UNDERSTANDING THE EFFECT OF CLIMATE CHANGE ON FISHERIES AND FISHING COMMUNITIES: A THEORETICAL AND AN EMPIRICAL APPROACH

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UNDERSTANDING THE EFFECT OF CLIMATE CHANGE ON FISHERIES AND FISHING COMMUNITIES: A THEORETICAL AND AN EMPIRICAL APPROACH

Samar Deen, Ph.D.

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This dissertation examines specific commercial fisheries in different geographic locations. The over-arching theme is to examine natural and/or anthropogenic perturbations in species dynamics. This dissertation also extends the association of species dynamics in perturbed systems to fisher based economies and human-health. Given the spatial and temporal nature of biological systems, spatial models and spatial-temporal models are applied to understand system dynamics with environmental stochasticity as a key determinant. An integrated nested laplace approximation spatial-temporal model explains fisheries abundance, (2) spatial bionomic models identify optimal management strategies in a changing fishery, (3) conditional auto-regressive models explain spatial differences in fisher well-being. This thesis will test whether distribution of the summer flounder can be explained by regional climate driven increase in ocean temperature in the Mid-Altantic Bight, USA; develops three models calibrated to the Maine, USA green sea urchin fishery *circa* 1995, that is used to test whether periodic closures are optimal to permit stock regeneration, or whether the creation of a marine reserve is optimal; provide empirical evidence to demonstrate a relationship between malnutrition in artisanal fisher communities an degradation in coral reef ecosystems in Indonesia. The results suggest that all management decisions take into consideration a precautionary approach that account for stochastic environmental events. Local sources of anthropogenic stressors should be mitigated, given that regional policies have a higher chance of ameliorating and off-setting global climate change stressors.

BIOGRAPHICAL SKETCH

Samar Deen is a PhD student in the Cornell University, Department of Natural Resources, holds a Masters in Public Administration from Cornell University, and a Bachelors in Computer Sciences from the Lahore University of Management Sciences, Pakistan. In her native Pakistan, she worked for the Punjab Government Planning and Development Department, UNICEF, the Polio program, Hagler Bailly Ltd (a private oil and gas environmental consultancy), Center for Economic Research Pakistan (an affiliate organization with the Jameel Poverty Action Lab, MIT), and at the World Bank on IT and health related digital transformation interventions. During her PhD she has consulted for the Himalayan Wildlife Foundation, Pakistan for brown bear conservation in the Deosai Plateau, the World Bank in the Environment and Natural Resources Unit, Washington D.C, on the Human Dimensions of Poverty Report, interned with the Environmental Defense Fund, Boston, on the Northeast Ecosystems Fisheries Project, and worked for the Department of Environmental Conservation, New York as a researcher on forest fragmentation in the Hudson River Valley. Her current research is on quantitative fisheries and resource economics.

This document is dedicated to my beautiful daughters Dina and Rania.

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" *Statistics are conclusive arguments. Nothing more practically educates the mind or tends more to rebuke and eradicate local or selfish prejudices than the undeniable lessons of statistical information.*" *The Statistician and Economist* (1896)

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CHAPTER 1

INTRODUCTION

The present rate of increase in atmospheric CO_2 is unprecedented in earths recorded history. Climate change is resulting in extreme precipitation events, river plumes and local corrosive events, increased stratification in oceans, increasing regional vulnerability to ocean acidification, sea surface temperature and coral bleaching. Each of these oceanographic changes impact fisheries and subsequently households that depend on fisheries as a source of livelihood. The main motivation behind my dissertation is to understand how specific oceanographic changes impact fisheries abundance, fisheries management at the regional scale and well-being at the household and community level.

Another motivation behind selecting each of these aspects is the different methodological approaches that will be utilized. Given the spatial and temporal nature of biological systems, spatial models and spatial-temporal models are useful analytical tools to understand system dynamics with environmental stochasticity as a key determinant. Broadly, I will use spatio-temporal models to understand changes in fisheries abundance, (2) spatial bioeconomic models to identify optimal management strategies in a changing fishery, (3) and apply a conditional auto-regressive model to identify spatial differences in well-being to regional covariate shocks such as coral bleaching events.

The evidence suggests that calcifying species such as the Green Sea Urchin *(Strongylocentrotus droebachiensis)* and Coral Reefs may be faced with an evolutionary challenge of adapting to the rapidly changing sea surface temperatures and ocean chemistry. The slow adaptation of the Maine cod fishery to the warming ocean is a case in point (Pershing et al., 2015). Conversely, even if species such as the the summer flounder *(Paralichthys dentatus)* thrive in warmer ocean temperatures, there are considerable implications on the spatial man-

agement of the species. SST increase is also directly impacting coastal fisher communities and economies that depend on these important species for commercial and recreation use.

It is important to understand how rising sea temperature, salinities, and changing ocean currents will interact with fishing pressure to affect fisheries productivity (Rose, 2005), and how fisheries management and fishing communities can be made more resilient to such changes. There is evidence suggesting that warming sea surface temperatures (SST) are shifting species' ranges and pushing marine fisheries poleward. In New England, species that have been mainstays of the ground fish fishery such as cod and yellow tail summer flounder have recently been observed moving northward (Pinsky & Fogarty, 2012), while species typically found in the Mid-Atlantic such as black sea bass and summer flounder are being found in the Gulf of Maine (Bell, Richardson, Hare, Lynch, & Fratantoni, 2015). Pershing et al. (2015) demonstrated that SST has a profound effect on the recruitment and survival of Atlantic cod. Failure to consider the impact of temperature has resulted in unrealistic estimates of the size of Cod stock biomass and its capacity to rebuild (Pershing et al., 2015). The changing environment will also alter human interactions with fisheries resources, as fishermen find themselves facing rapidly changing abundance and distribution of target species. These changes will affect the profitability of the fishery, and may effect the region's fishing communities as fishermen change their target species, gear, or fishing behavior.

More specifically, I evaluate the biological and economic consequences of rising sea surface temperature (SST) on species such as the summer flounder *(Paralichthys dentatus)* in the U.S. Mid-Atlantic Bight and the green sea urchin *(Strongylocentrotus droebachiensis)* in New England, both of which have considerable cultural and economic value. I also evaluate the relationship between SST increase and interaction effects of anthropogenic stressors on malnutrition in fisher communities.

This dissertation consists of three chapters that cover the main themes mentioned earlier, i.e. how specific oceanographic changes impact fisheries abundance, fisheries management at the regional scale and well-being at the household and community level. Chapter 2: The effect of ocean temperature on the abundance of fish: A case-study of the summer flounder *(Paralichthys dentatus)* from the U.S. Mid- Atlantic Bight, evaluates climate resiliency in the summer flounder fishery. Elevated CO_2 levels in the ocean can alter the survival, growth, and development of early life stages of summer flounder (Chambers et al., 2014). Climate change may result in the summer flounder shifting its range to a sub-optimal habitat (Bell et al., 2015). Changing temperature regimes may also influence sex-differentiation (H. R. Colburn, Breton, Nardi, & Berlinsky, 2015). This chapter tests whether there is a northward shift in the distribution of the summer flounder in response to regional climate driven increase in ocean temperature. I also test whether the localized spatial pattern of abundance is driven by temperature and other environmental factors.

Chapter 3: Pure Open Access and Spatial Management in a Two-Zone Fishery, evaluates the management options for increasing resilience of a fishery that may have declined to a unstable equilibrium. The green sea urchin is an important commercially valuable species in Maine (Chen, Hunter, Vadas, & Beal, 2003). Experimental evidence has demonstrated that increase in SST will impact the growth and development, of the green sea urchin (Siikavuopio, Mortensen, & Christiansen, 2008). The green sea urchin abundance and landings in the Northeast have significantly reduced since the late 1980s and 1990s and have yet to recover (Figure:1.1). The green sea urchin population has been over harvested, threated by kelp deforestation and the crab *(Cancer spp.)* - a micro predator (Steneck et al., 2002). The green sea urchin fishery is threatened by ecological and anthropogenic stressors, which are most likely interacting to reduce the likelihood of recovery.

This chapter develops three models calibrated to the Maine green sea urchin fishery *circa*

1995. These three models are developed to test the system dynamics that have led to a decline in this fishery, (1) a two-zone, pure open access model, with larval dispersion (2) a two-zone, pure open access model, with larval dispersion with an objective function tracking Hunter (2015) biomass estimates, and (3) a dynamic mixed integer model that maximizes the present value of net revenue. The models are used to test whether periodic closure of Zones 1 or 2 would be optimal to permit stocks to rebuild, or whether the creation of a marine reserve would be optimal. The ultimate question I explore is whether the Maine coastal ecosystem supports two stable steady states, one with high urchin biomass (low kelp and crab biomass), and one with low urchin biomass (high kelp and crab biomass). The objective is to determine whether over-harvesting in the Maine green sea urchin fishery may have "flipped "the ecosystem into an economically less desirable equilibrium.

Chapter 4: Marine Resource Degradation and Malnutrition. A Spatial Community Model of Well-being in Small-scale Fisher Communities in Indonesia, explores the social-ecological relationships in a changing global environmental. Global environmental "systemic "threats to the Coral Triangle include, burning of fossil fuels, deforestation, land-use change, climate change induced ocean warming and acidification. These systemic threats are altering the chemical and physical attributes of the marine ecosystem where coral reefs, mangroves and sea grasses provide vital ecosystem services. Local threats include anthropogenic activities that are localized, including declining water quality, over-exploitation of resources, sewage discharge, destructive fishing, and over fishing, which is threating over 65% of the coral reef (Hoegh-Guldberg et al., 2009). These stressors threaten not only biodiversity and ecosystem integrity but also the health and livelihoods of the coastal communities that dependent on them. What are some of the determinants of this spatial variation in extent of fisheries productivity? Climate driven coral bleaching is emerging as one of the greatest threats to the coral reef ecosystem (Graham et al., 2007). Coral reefs are being degraded at an

accelerated pace due to local-scale and global-scale stressors mentioned earlier. In the past decade we have already experienced two massive global coral bleaching events (See Figure 1.2). Consequently, coastal fishermen communities are expected to be greatly impacted by these events (UNEP, 2006). It is estimated that approximately 95% of the total fishing fleet production consists of small-scale, undocumented fisheries in Indonesia (Hoegh-Guldberg et al., 2009). These resources are vital for the well-being of coastal communities. The extent of dependence on the resource varies geographically (Figure:1.3). Given that there is high dependence on fisheries as a main source of income, Indonesia is and ideal case to study the linkages between fishing dependent villages and well-being (as measured by malnutrition) Chapter 4 provides empirical evidence to demonstrate a relationship between malnutrition in artisanal fisher communities an degradation in coral reef ecosystems. A secondary objective is to identify the relevant determinants of well-being in fisher communities.

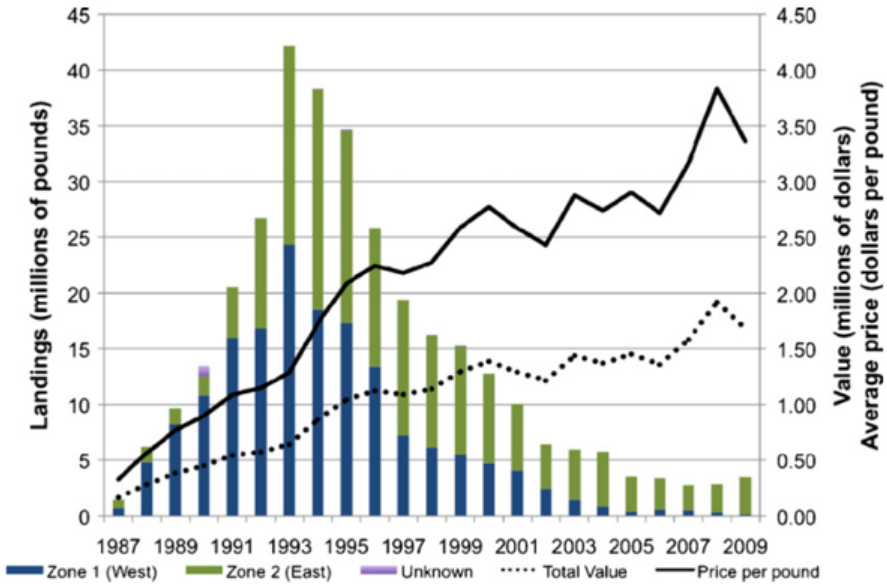

Figure 1.1: Maine sea urchin landings by zone and value and prices from 1987 to 2009 Maine Department of Marine Resources; (T. R. Johnson et al., 2013)

The questions in all the three chapters stated above have been addressed using secondary data sources. These include, the National Marine Fisheries Service (NMFS) trawl survey

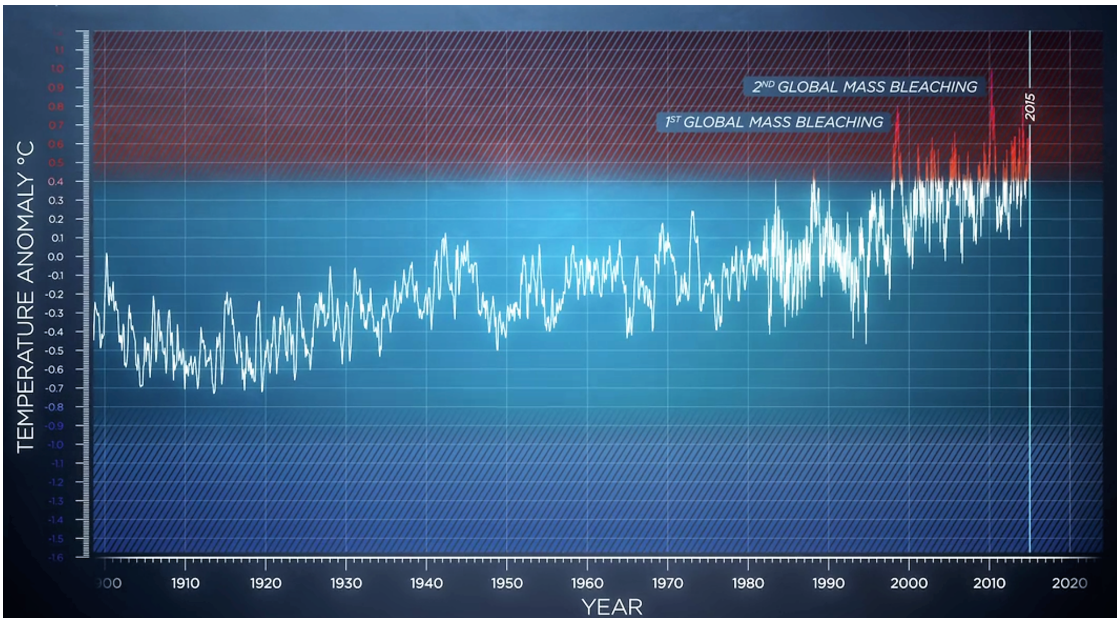

Figure 1.2: Sea Surface Temperature Anomaly (Orlowski, 2017)

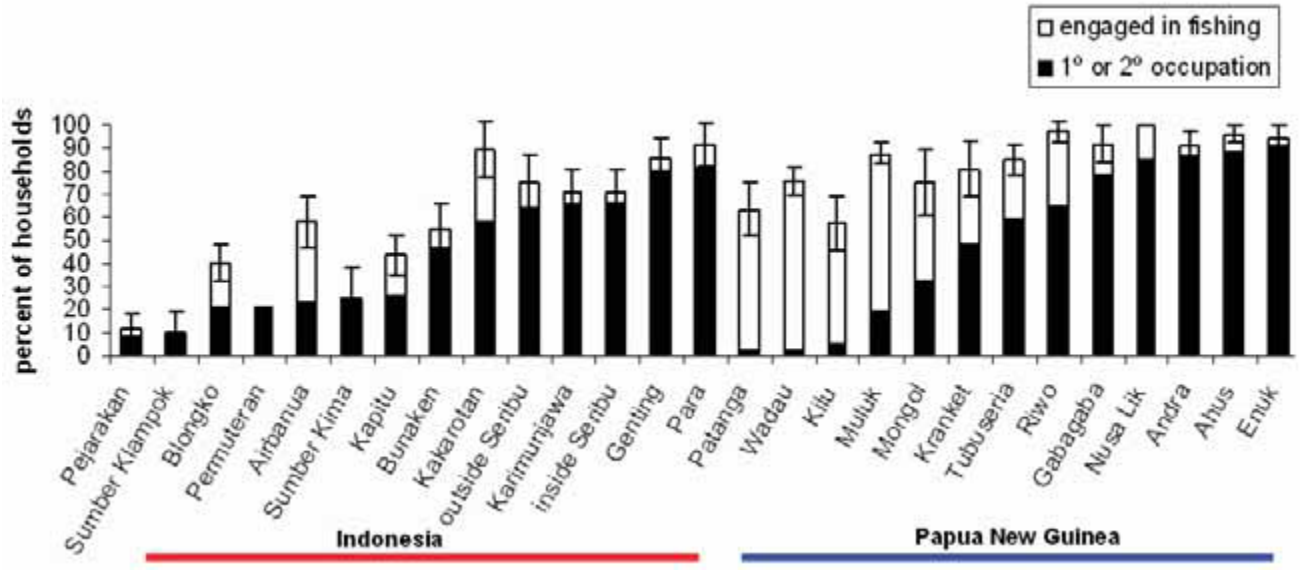

Figure 1.3: Percentage of households engaged in fishing (Hoegh-Guldberg et al., 2009)

data, oceanographic satellite derived NOAA datasets for the summer flounder fishery. A meta-analysis of biological and economic parameters is conducted to parameterize the bioeconomic models in order to calibrate the model to the green sea urchin fishery. A nationally representative socio-economic dataset, Indonesian Family Life Survey (IFLS) Panel Dataset (1997 – 2015), the Village Potential Statistics (PODES) dataset (2007-2015), and the Reefs at Risk database containing ecological and anthropogenic threats on coral reefs compiled by the World Resources Institute. The NOAA Coral Reef Watch SST products such as degree heating week are used to quantify the severity of coral bleaching events.

CHAPTER 2

THE EFFECT OF OCEAN TEMPERATURE ON THE ABUNDANCE OF FISH: A CASE-STUDY OF THE SUMMER FLOUNDER *(PARALICHTHYS DENTATUS)* FROM THE U.S. MID- ATLANTIC BIGHT

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We examine the spatial distribution of summer flounder (*Paralichthys dentates*) and its relationship with various ecological covariates. Conditional autoregressive (CAR) models and the integrated nested laplace approximation (R-INLA) approach are used to account for the random effects arising from either over-dispersion, or spatial and temporal autocorrelation. The summer flounder abundance data is represented as spatial areal unit count data. We explore how the different assumptions in the spatial temporal models result in varying model predictions. The paper mainly describes the effect size of the Fall season, but a similar analysis was done for the Spring season as well. Fish abundance data and oceanographic data were collected during National Marine Fisheries Service (NMFS) Fall and Spring bottom trawl surveys. Satellite derived sea surface temperature (SST) were accessed from the Advanced Very High Resolution Radiometer Pathfinder SST time series (1985-2009) and the Aqua MODIS 11μ nighttime SST time series (2010-2015) as provided by NOAA's National Environmental Satellite, Data and Information Service. The results indicate that the distribution of summer flounder stock is correlated with a regional-climate-driven increase in ocean temperature and bottom-salinity. An analysis of the Fall and Spring 1991-2014 data suggests

that the effect size of bottom temperature during the Fall Season on abundance ranges from $7 - 60\%$ (without bias correction). The SST has a higher effect size $5 - 38\%$ on summer flounder abundance during the Spring Season, even after accounting for over-dispersion, and spatial-temporal autocorrelation.

2.1 Introduction

The unprecedented rate of increase in atmospheric CO_2 has resulted in significant changes in ocean temperature and chemistry (Branch, DeJoseph, Ray, & Wagner, 2013). This suggests that fish species may have to adapt to a rapidly changing environment. It is important to understand how rising sea temperature, salinities, and changing ocean currents along with overfishing will interact to affect fisheries productivity (Rose, 2005), and how fisheries management and fishing communities can be made more resilient to such changes. Research is suggesting that warming sea surface temperatures (SST) are shifting species' habitat ranges and forcing many marine fisheries to move poleward. In New England, species that have been mainstays of the ground-fish industry such as cod and yellowtail flounder may be moving northward (Pinsky & Fogarty, 2012), while species typically found in the Mid-Atlantic such as black sea bass and summer flounder are now being found in the Gulf of Maine (Pershing et al., 2015). Pershing et al. (2015) examined the impact of SST on the recruitment and survival of the Atlantic cod. They showed that the rebuilding potential of Atlantic cod differed greatly under different temperature scenarios depending on the effect that temperature had on mortality, growth and recruitment of cod. Nye, Link, Hare, and Overholtz (2009) conclude that a failure to consider the impact of temperature could have contributed to unrealistic estimates of the size of the cod stock biomass and its capacity to rebuild. Rapid changes in local and total abundance, and species composition will affect fishers ability to meet harvesting quotas in areas where abundance is declining. It may result in fishers targeting different species, which would require switching fishing gears, or they may decide to leave the fishery altogether. These changes will affect the profitability of the fishery, and may have economic implications on predominantly fishery dependent communities. Alternatively, fishers may attempt to harvest outside their state boundaries in regions where the fishery is more abundant, creating conflicts over quotas and catch limits

across different states (Hobday, Bell, Cook, Gasalla, & Weng, 2015).

These concerns are particularly relevant to the summer flounder fishery. There is some evidence to suggest that there is an increase in biomass (Terceiro, 2017), area occupied, and a poleward shift in distribution of the summer flounder in response to an increase in sea surface temperature (Nye et al., 2009). The summer flounder larva and juveniles mortality are sensitive to temperatures below 2°C, suggesting that warmer winters in the northern part of the range will result in higher overwintering survival (Bell, Hare, Manderson, & Richardson, 2014). It can be expected that with warming ocean temperatures, estuaries in the northern range will expand the area of suitable habitat, resulting in higher recruitment and increase in stock abundance (Able et al., 2010).

In contrast, some would argue that reduced fishing pressure is the main determinant for the increase in summer flounder abundance further north (Bell et al., 2014; Lavelle, 2014). One approach to understanding time-varying spatial trends in fisheries is to use statistical models that examine the occurrence of fish species as a function of environmental covariates (temperature, depth, salinity, longitude and latitude). Integrated Nested Laplace Approximation (R-INLA) models and stochastic partial differential equations (SPDE) have recently been used to fit zero-inflated hierarchical spatial-temporal models. For example, studies have used R-INLA spatial-temporal models to characterize variations in population density of pelagic sharks to predict spatial distribution (Kai, Thorson, Piner, & Maunder, 2017) and identify temporally evolving hot spots of species co-occurrence (Ward et al., 2015). Cosandey-Godin, Krainski, Worm, and Flemming (2015) have used these methods to model the spatial-temporal patterns of Greenland shark bycatch in the Canadian Arctic. Similar to the summer flounder data, bycatch data are characterized by complex statistical features, such as excess of zeros, nonlinearities, non constant variance structure, and spatial-temporal correlation . Other studies have focused more on the spatial-temporal variation in human

impacts while accounting for individual movement using fishery logbooks to estimate the spatial distribution of fishing effort (Thorson, Jannot, & Somers, 2016).

For this paper, we examine the spatial distribution of the summer flounder *(Paralichthys dentates)* relative to sea surface temperature (SST), bottom temperature, depth, season, and salinity for the years 1991-2015. We fit the data to various spatial, and spatial temporal models to determine which models would best characterize our data. The proposed scientific objectives of this analysis are to: (1) Identify the ecologically significant physical oceanographic covariates that best explain the presence of the Mid-Atlantic summer flounder (fluke); and (2) Provide a critique of spatial temporal modeling and its application to characterizing fisheries data.

Summer flounder is a demersal flatfish abundant in the Mid-Atlantic Bight and found in the region between Cape Cod and Cape Hatteras. It has also been found in the Gulf of Maine southward to Texas (Poole, 1961). The adult summer flounder are found close inshore in the bays and estuaries from late Spring to early autumn, during their on-shore migration to breeding grounds in the estuaries areas of Pamlico Sound and Chesapeake Bay (Packer et al., n.d.). Spawning occurs during the fall and winter while the fish move offshore to their wintering location. The larvae drift and migrate inshore to the coastal and estuarine nursery areas. The exact timing of migration, especially to and from estuaries, varies in response to environmental factors such as barometric pressure, dissolved oxygen and temperature with its presumed effect on metabolic rate (Sackett, Able, & Grothues, 2007). The development of the larval and juvenile stages occurs in the bays and estuaries (Packer et al., n.d.). The summer flounder reaches sexual maturity around age two (O'Brien, Burnett, & Mayo., 1993), the median length at maturity is estimated at 26.0 cm for male summer flounder and 29.2 cm for the females (Northeast Fisheries Science Center, 2013). Previous research suggested that the males are heavier than the females for any given length (Lux & L.R. Porter, 1966),

however, males rarely live longer than 10 years. In the Spring, the adults occur at a range of temperatures from 6-17 °C, while in the fall they occur at temperatures from 14-21 °C Packer et al. (n.d.). The abundance is highest at depths between 18- 27 m in October and depths 27 m in November (Northeast Fisheries Science Center, 2013). The summer flounder exhibits sexually dimorphic growth rates. The females grow at a faster rate and are 1.4 time larger than males at 15 months post-hatch. The females are usually twice as large as the males at 23 months (H. R. Colburn, Nardi, Borski, & Berlinsky, 2009; King, Nardi, & Jones, 2001; Morse, 1981). The females live up to 20 years, reaching weights of about 25 lbs (Northeast Fisheries Science Center, 2013).

Laboratory studies on summer flounder have shown that growth rates increase with increasing salinity (J. Burke, Miller, & Hoss, 1991; Rogers & Van Den Avyle, 1983), and temperatures between 5-21 °C promote faster development of the embryo and yolk sac larvae. Temperatures below 11 °C are considered lethal. Overall, temperature has a pronounced effect on growth efficiency, feeding rate and assimilation of the juveniles (Grimes, Huish, Kerby, & Moran, 1989). Laboratory studies of temperature manipulation have also suggested that during the critical phase preceding gonadal development, temperature regimes from 21–26°C can influence sex differentiation in summer flounder (H. R. Colburn et al., 2009).

The growth rates of summer flounder are also affected by the interaction effects of anthropogenic stressors. In addition to SST, other stressors are also known to impact the habitat suitability of the summer flounder. The summer flounder occurs in estuarine and coastal shelf waters in the North Atlantic, spanning from Nova Scotia to Florida (Able & Kaiser, 1994). The degradation of estuarine habitats is a common threat to estuary dependent fishes such as the summer flounder which utilize estuaries as a nursery habitat (Stierhoff, Targett, & Miller, 2006). Stierhoff et al. (2006) studied the response of juvenile summer flounder to hypoxia and other factors influencing estuarine quality. The research indicated that

growth rates were generally reduced as dissolved oxygen decreased ($50-70\%$ air saturation) and as temperature increased. Eutrophication (Rabalais, Turner, Díaz, & Justić, 2009); (Gulf of Maine Council on the Marine Environment, 2012), hypoxia (Pörtner, Langenbuch, & Michaelidis, 2005) and acidification (Blackford, 2010) are looming threats to estuarine environments. Experimental work (Chambers et al., 2014) revealed that larval size and development even under intermediate CO_2 levels are affected. Although these stressors and their interaction effects are important when considering spatial and temporal occurrence, we will not be studying the estuarine linkages of multiple stressors and their interaction effects (S. L. Smith, Cunni, Peyronnin, & Kritzer, 2017) on summer flounder abundance.

Here we will use recent advances in spatial temporal modeling to better understand the underlying spatial variations in summer flounder abundance using the annual Fall and Spring trawl surveys as data inputs. These surveys are used as an indicator of the abundance and spatial location of the fish. Variations in summer flounder distribution, based on National Marine Fisheries Service Fall and Spring surveys, will be compared with variations in sea surface temperature (SST) from satellite remote sensing for the eastern US continental shelf for the period 1985–2014. We hypothesize that the localized spatial pattern of abundance is correlated with ocean temperature and salinity, even after taking into account the spatio-temporal correlation that exists in such processes.

2.2 Management of the Summer Flounder Fishery

The summer flounder is an economically important flatfish for commercial and recreational fisheries in the Mid Atlantic (See Figure 2.2). In the late 1980s, the Atlantic coast summer flounder stock was considered over fished (NEFC, 2002). The total annual landings of

summer flounder peaked at 18,000 metric tons (mt) in 1980. Commercial landings fell from 38 million pounds in the 1980s to as low as 9 million pounds by 1990. In the recreational fishery there was a decline from 30 million pounds to about 3 million pounds over this same time period. The landings in (1990–2006) declined, fluctuating from 4000 mt to 6300 mt. The Mid-Atlantic Fishery Management Council and the Atlantic States Marine Fisheries Commission in the late 1980s to the early 1990s implemented management measures such as reduced quotas, and size limits to reduce fishing mortality and increase the spawning stock biomass. As a result of this and favorable environmental conditions there has been a subsequent rise in the abundance of the fishery. Approximately 20 million pounds of summer flounder are now caught annually, with the commercial fishery getting approximately 60% of the share. Not surprisingly, this increase in abundance is reflected in the annual bottom trawl surveys as shown in Figure 2.1

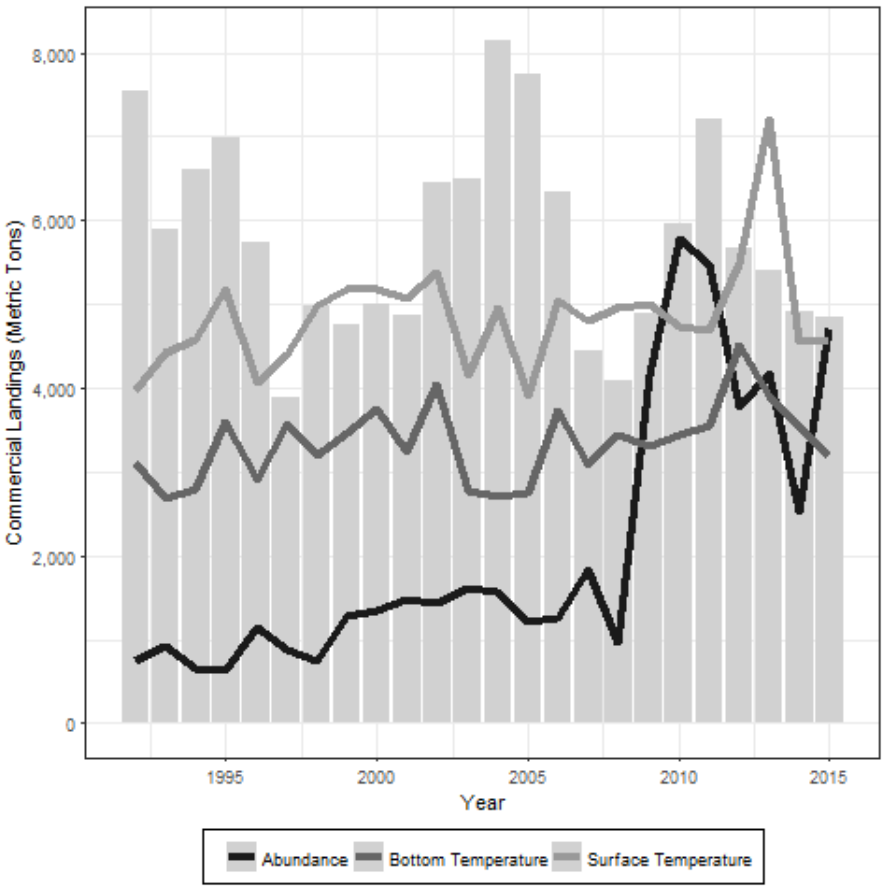


Figure 2.1: Landings, Bottom Temperature ([min = 5.3, max = 9.0 °C]), Surface Temperature ([min = 7.8, max = 14.4 °C])and Spring Trawl Survey in Albatross Units ([min = 105, max = 810]) (1991 − 2015)

2.3 Data

We use two main data sets to carry out this analysis. The first dataset pertains to the annual relative abundance of summer flounder and is collected three times a year by the National Marine Fisheries Service (NMFS). The NMFS survey samples the Atlantic continental shelf from North Carolina to Nova Scotia annually during March-June for the Spring survey, the Fall survey is conducted during September-October. This survey determines fish abundance by administrative region. There are approximately 310 administrative regions on the At-

lantic Continental shelf as surveyed by the NMFS 2.2. The bottom trawl survey also records environmental variables, such as bottom and surface temperature, bottom and surface salinity, depth, wave height, wind strength and direction. The second dataset pertains to the satellite derived SST. Satellite derived SST is accessed from the Advanced Very High Resolution Radiometer Pathfinder Version 5 SST time series (1985-2009) and the Aqua MODIS 11μ nighttime SST time series (2010-2015) as provided by NOAA's National Environmental Satellite, Data and Information Service NASA Goddard Space Flight Center (2016). The AVHRR Pathfinder Version 5 data is obtained from the Physical Oceanography Distributed Active Archive Center (Physical Oceanography Distributed Active Archive Center, 2015).

The data editing process for temperature involved acquiring the SST data from the satellite NetCDF files by administrative region (Figure 2.3) and matching them to NMFS survey data by administrative region ID, Year, Season. These data were imported into the R Statistical software for further data structuring and statistical modeling. The x and y coordinates represent the centroids of each administrative region acquired from the shapefile. Bathymetry is also averaged across each region. The response variable is an index of the number of fish found in each region by year and season. We use summer flounder abundance in Albatrose Survey Vessel (ALB) units to determine the marginal effects of environmental and spatial covariates. This summer flounder data set includes spatial, temporal, zero-inflated count data, and hence we characterize it using a zero-inflated Poisson distribution.

The data in ALB units of summer flounder abundance can be compared by administrative region in Spring 2014, with maximum SST in Figure 2.4. The gray areas represent 0 fish (recorded by the NMFS trawl survey) in the extreme north and south of the administrative regions. The bottom and surface temperatures recorded by the bottom trawl survey vessel, and the 3-month composite from satellite are summarized in Figure 2.5. Statistical comparison shows that the bottom temperature and the 3-month composite surface temper-

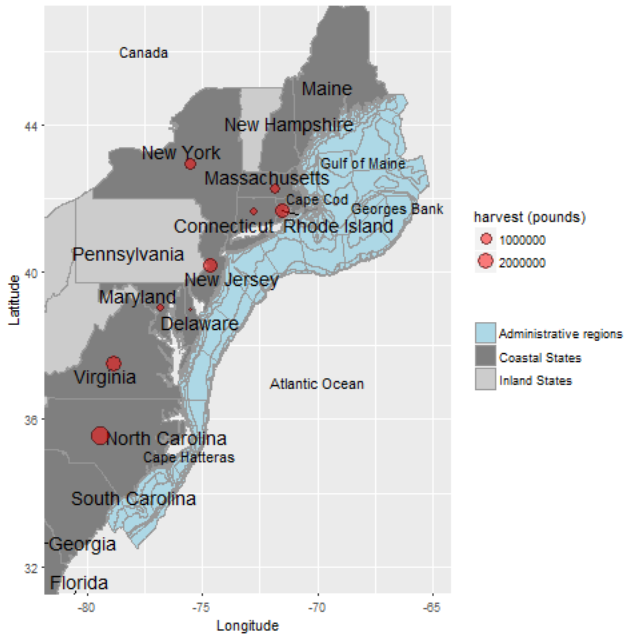


Figure 2.2: Annual Harvest by State in Year (2015), Mid Atlantic Bight, USA

ature (SST) recorded from satellite are statistically significantly different from each other. Therefore we will use both SST and BT in our regressions to get an understanding of which has a greater influence on abundance. A statistical comparison of temperature and season also reveals that there is a statistically significant difference in temperature between seasons. Therefore we run separate models for both Fall and Spring seasons.

In the fisheries literature, satellite data characterizing SST and surface concentrations of chlorophyll *a* are used extensively to map primary productivity and to assess the spatial ecology of marine top predators. A recent study concluded that there is a significant spatial overlap between marine top predators and zones of intense primary productivity (Grémillet et al., 2008). However, this positive correlation does not appear to exist for intermediate trophic levels. Satellite based SST data also has limitations that can reduce its applicability. Cloud cover and regions that are located too close to the coast often cannot be interpreted accurately. Here we flag such data as low quality and masked it out as unavailable.

Abundance data along with the SST merged dataset were analyzed in R Version 3.3.1 – ©2016 (R Core Team, 2016). The spatial-temporal analysis was conducted using the R-package R-INLA version 0.0 − 1463562937 (Lindgren & Rue, 2015; Lindgren, Rue, & Lindström, 2011; Martins, Simpson, Lindgren, & Rue, 2013; Rue, Martino, & Chopin, 2009), used within the R statistical environment R Version 3.3.1 – ©2016 (R Core Team, 2016).

Abundance is represented as an area-weighted average in ALB units across the different statistical regions. For each spatial unit, an expected average is also computed. The expected average will be used in the R-INLA package as the offset E_i for each spatial unit (discussed later).

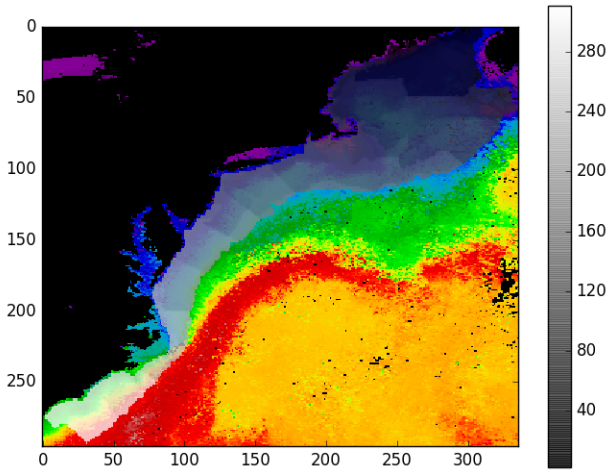


Figure 2.3: Mid Atlantic Bight Sea Surface Temperature 3 Month Composite with Administrative STRATA

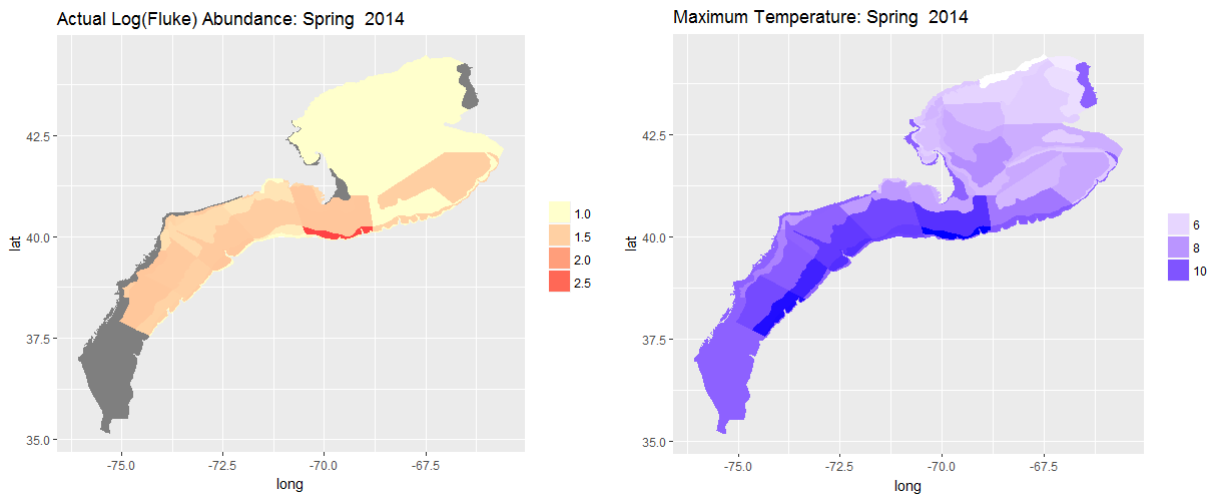


Figure 2.4: Maximum Temperature and Fluke Abundance by Administrative Regions, Mid Atlantic Bight, USA

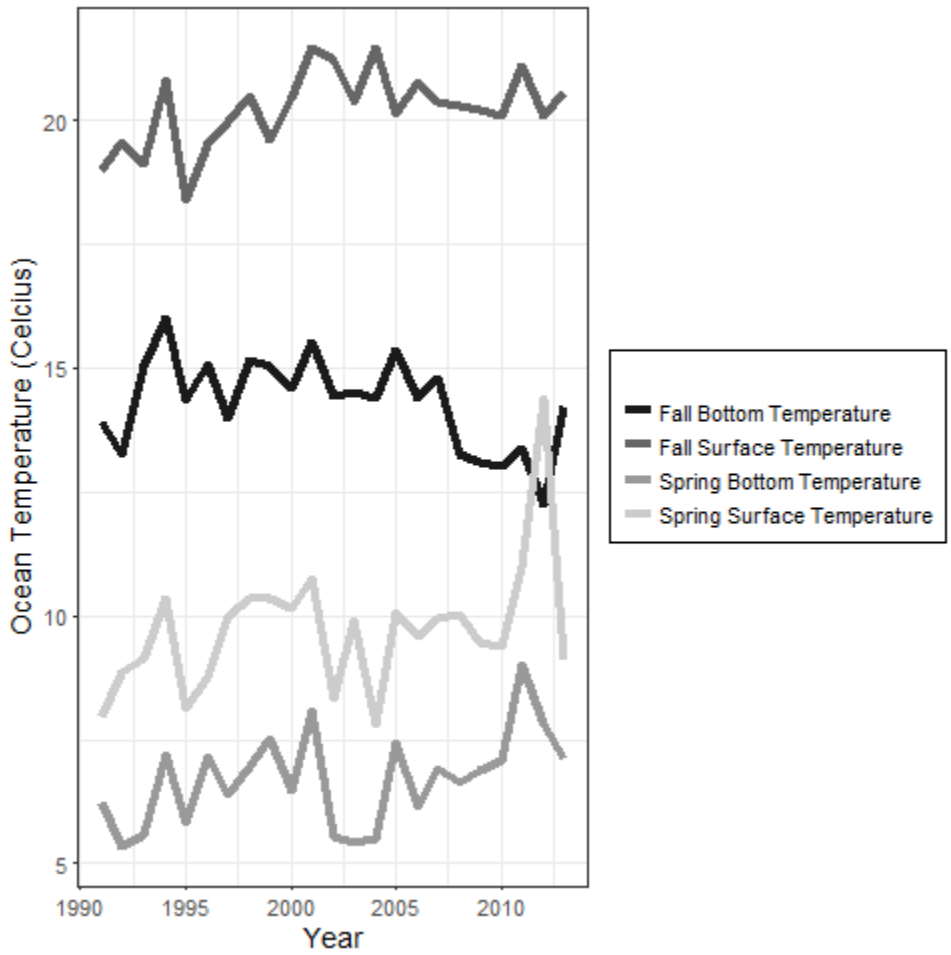


Figure 2.5: Average Fall and Spring Temperatures, Mid Atlantic Bight, USA (NMFS Trawl Survey, NASA Goddard Space Flight Center (2016))

2.4 The Model

A Poisson nonparametric model is used to characterize change in abundance y_i as a function of time, space and environmental covariates following the ideas in Blangiardo and Cameletti (2015). We characterize the relative abundance as $y_i \sim Poisson(\lambda_i)$, which we consider as the weighted catch per tow of flounder. y_i is a continuous variable that can assume values between 0 and ∞ modeled using a Poisson distribution, with expected relative abundance by area, λ_i. The log linear model is denoted as,

$$\eta_i = log(\lambda_i) = \alpha + \upsilon_i + \nu_i \tag{2.1}$$

where α is the intercept quantifying the average number of flounder per tow over the entire 108 administrative regions. The spatially structured correlation is υ_i. The independent spatial variation considered unstructured is ν_i. These two area specific (spatial) effects are described further in the section below. The indicator for each administrative region is $i = 1, ..., n$.

2.4.1 Conditional Autoregressive Model

In this paper we implement a conditional autoregressive (CAR) structure to account for adjacent area specific effects. The intrinsic conditional autoregressive (iCAR), also known as BESAG, proposed by Besag, York, and Mollié (1991) is denoted as

$$\upsilon_i | \upsilon_{-i} \sim N(\mu_i + \frac{1}{\mathcal{N}_i} \sum_{j=1}^{n} a_{ij}(\upsilon_j - \mu_j), s_i^2) \tag{2.2}$$

where υ_i is the spatial autocorrelated spatial residual, n is the number of areas characterized by a set of neighbors, $\mathcal{N}(i)$, μ_i is the mean abundance of neighborhood set, $s_i^2 = \sigma_u^2/n_i$ is the variance of the estimate, a_{ij} is 1 for each neighbor in the neighborhood set, and 0 otherwise. The parameter σ_u^2 controls the level of variation between the spatially structured random effects. For this paper, a neighborhood is defined as administrative regions (areas) that share a common border with the central administrative region under consideration. Therefore, in the CAR models, a common border based neighborhood approach is consistently used. These common border neighborhoods are identified based on the spatial polygons provided by the administrative shape file, and saved in a graph file accessible to both the spdep and R-INLA functions.

Besag et al. (1991) also proposed the Besag-York-Mollié (BYM) model, where υ_i is the spatial autocorrelated spatial residual, modeled using an intrinsic conditional autoregressive model (iCAR), and the parameter ν_i is the unstructured independent residual, $\nu_i \sim N(0, \sigma_\nu^2)$. When $\mu_i = 0$ for each i, the conditional distribution for υ_i is formulated as,

$$\upsilon_i | \upsilon_{-i} \sim N(\frac{1}{\mathcal{N}_i} \sum_{j=1}^{n} a_{ij}\upsilon_j, s_i^2) \tag{2.3}$$

Therefore the iCAR along with ν_i, the exchangable random effect presented in Equation 2.1, forms the BYM model (Besag et al., 1991).

Cressie (1993) proposes an alternative model with an additional spatial correlation parameter, ρ, which controls the strength of the spatial correlation between the random effects. When $\rho = 0$, the random effects would be considered independent. The Cressie (1993) model is denoted as,

$$\upsilon_i|\upsilon_{-i} \sim N(\rho\frac{1}{\mathcal{N}_i}\sum_{j=1}^{n}(1-\rho)a_{ij}\upsilon_j, s_i^2) \tag{2.4}$$

where an increasing value of ρ, will indicate strong spatial correlation, and $\rho = 1$ will be equivalent to the iCAR model.

The Conditional Autoregressive (CAR) model is computed using R-Package *spdep* version $0.5-92$ (Bivand, 2007), following the specification in Cressie (1993). The BESAG and BYM specifications in Besag et al. (1991) are embedded in the R-INLA spatial temporal models.

2.4.2 Bayesian Spatial Temporal Models

Given that our data set is comprised of count data with an excess of zeros, regular Poisson or Gaussian models may be inappropriate, as the excess of zeros will result in overdispersion. The Poisson models are typically characterized by a single parameter for both the mean and variance. An alternative zero-inflated Poisson model can be constructed to account for the binary distribution of zeros and conditional distribution of abundance at non-zero locations to account for a point mass at zero associated with a condition count distribution. These models distinguish between structural zeros (where zero is the only observable value), and sample zeros (where zeros may be observed along with count data). While the R-INLA package implements various models, the CAR model in the spdep package only implements models that include a Gaussian distribution.

We appropriately characterize this dataset as spatial, temporal, with a zero-inflated Poisson distribution. We implement this model using the integrated nested Laplace approximations (R-INLA) to implement the hierarchical Bayesian approach to fit the data (Rue & Martino, 2010). We can capture heterogeniety in the data using a hierarchical character-

ization of the spatial structure. Overdispersion is dealt with by combining the temporal structure with the Zero Inflated Poisson (ZIP) Model.

The main advantage of a hierarchical Bayesian approach resides in its taking into account uncertainty at several levels in the estimation process, for example the uncertainty in the estimates of both trend and correlation parameters and its ability to deal with issues like missing data. In order to overcome the computational complexities associated with Bayesian inference via Markov Chain Monte Carlo (MCMC) which are implemented by many Bayesian procedures incluing the CARBayes package by Lee (2013), R-INLA, a deterministic algorithm proposed by Rue and Martino (2010) that integrates the marginal probabilities by applying a Laplace approximation to the Gaussian latent variables is used. Under certain broad assumptions, this method ensures faster calculation of the posterior distribution than can be found under the computationally intensive MCMC methods for the latent Gaussian class of models.

We implement models for the latent Gaussian field in the software R-INLA (Lindgren & Rue, 2015; Lindgren et al., 2011; Martins et al., 2013; Rue et al., 2009). This software includes model formulations with independent random variables (iid), random walk of order 1 or order 2 (RW1, RW2), a model for spatial effects (BESAG), and models with spatial and random effects (BYM). The Besag-York-Mollié (BYM) model (Besag et al., 1991) as explained earlier is a union of the BESAG model (Besag et al., 1991) where υ_i is the global intercept with a spatially structured area specific effect, and an iid model, where ν_i is the unstructured area specific effect, with $i = 1, ..., n$ as the indicator for each administrative region (spatial area). The spatially independent variation is applied to ν_i.

These models are implemented within a hierarchical structure. In the first level of the hierarchy, $log(y)$ is the sampling distribution, factorized as $y_1, ..., y_n$. The y are exchangeable

and iid, given the latent field θ (regression parameters) and hyper-parameters ψ (measurement error precision). In the second level, the latent field θ is characterized by a MVN given the remaining hyper-parameters ψ_2. The hyper-parameters $\psi \sim p(\psi_2)$ have the prior distribution given by $\psi = \{\psi_1, \psi_2\}$. The fixed effects are the intercept α , bottom salinity, ocean depth (Bathymetry), surface temperature, and bottom temperature. The random effects are δ_{it} (ID.area.year, iid model), ϕ_t (ID.year, iid model), υ_i (ID.area, BYM model), and γ_t (ID.year, RW2 model), and the hyper-parameters are τ_υ , τ_ν , τ_γ, τ_ϕ and, τ_δ.

The spatial temporal nonparametric model is based on the models specified in Blangiardo and Cameletti (2015). Consider the count of summer flounder y_i, a discrete variable that can assume values between 0 and ∞ modeled using a zero-inflated Poisson distribution. Within the n administrative regions the probability function for $y_i (i = 1, ..., n)$ is,

$$p(y_i|\lambda_i, \pi_0) = \pi_0 I(y_i = 0) + (1 - \pi_0) + exp(-\lambda_i)\lambda_i^{y_i}/y_i! \tag{2.5}$$

where y_i is the observed summer flounder count at location i, $I(y_i = 0)$ is the indicator variable. The probability of observing a zero in administrative area is $\pi_0 + (1 - \pi_0)exp(-\lambda_i)$. The mean is $E(y_i) = (1-\pi_0)\lambda_i$, and variance is $Var(y_i) = (1-\pi_0)\lambda_i + \pi_0((1-\pi_0)\lambda_i)/(1+\pi_0)$. Then conditional on y_i being a sample zero, the log-transformation of λ_i is denoted by Equation 2.1.

To evaluate the relationship between ecological covariates (e.g, bottom temperature) and summer flounder abundance in each STRATA, we extend the model in Equation 2.1 to,

$$log(\lambda_i) = \alpha + \beta_1 x_{1i} + \upsilon_i + \nu_i \tag{2.6}$$

where the fixed effects (α, β_1), if exponentiated can be interpreted as covariates on the relative incidences of fish presence. The matrix x_i is comprised of ecological covariates, bottom temperature, salinity, surface temperature and depth.

In all space-time models, the distribution of hyper-parameters is $id \sim$ Normal $(0, 1/\sigma^2_{\upsilon_0})$, where $\log(1/\sigma^2_{\upsilon_0}) \sim \text{logGamma}(1, 0.0005)$, specifically, $\text{logGamma}(\alpha, \beta)$ is $\log\ \tau_\upsilon \sim \text{logGamma}(1, 0.0005)$ and $\log\ \tau_\nu \sim \text{logGamma}(1, 0.0005)$ along with a $\text{logGamma}(1, 0.0005)$ prior on the precision of the random walk and the two unstructured effects. Table 2.1 summarizes the linear, CAR and the spatial-temporal models.

Model	$\delta_{i,t}$[a]	Description
1	-	Linear Regression with Year and spatial coordinates as fixed effects
2	-	Conditional Autoregressive (BYM) with linear combination of ν_i, υ_i. Year as fixed effect
3	-	Zero-Inflated Poisson Model (ZIP) with BYM (ν_i, υ_i) and Year as factor
4	-	ZIP with BYM (ν_i, υ_i) and ϕ_t as the temporal unstructured effect
5	-	ZIP with linear combination of ν_i,ϕ_t, γ_t, and υ_i
6	ν_i,ϕ_t	ZIP with ν_i as spatial unstructured effect, ϕ_t as the temporal unstructured effect with Rank[b]: nT
7	ν_i,γ_t	ZIP with ν_i as the unstructured spatial effect, γ_t as the structured temporal effect with Rank: $n(T-1)$, RW1 and $n(T-2)$, RW2
8	υ_i,ϕ_t	ZIP with υ_i as the spatial structured effect, ϕ_t as the temporal unstructured effect with Rank: $(n-1)T$
9	υ_i,γ_t	ZIP with υ_i as the spatial structured effect, γ_t as the temporal structured effect with Rank: $(n-1)(T-1)$, RW1 and $(n-1)(T-2)$, RW2

[a]The differential trend, $\delta_{i,t}$ identifies the interaction between space and time
[b]Rank of Kronecker product

Table 2.1: Model Summary

The best model is identified using the Deviance Information Criterion (DIC) (Spiegelhalter, Best, Carlin, & Van der Linde, 2002). The DIC is a measure of model fit developed for Bayesian comparison. The DIC consists of two components. The first component, $D(\theta) = -2log(p(y|\theta))$, quantifies model fit. The second components measures model complexity through the effective number of parameters, $p_D = E_{\theta|y}(D(\theta)) - D(E_{\theta|y}(\theta)) = \bar{D} - D(\bar{\theta})$. The DIC is

$$DIC = \bar{D} + p_D \tag{2.7}$$

Similar to the Akaike Information Criterion (AIC), the models with smaller DIC indicate a better fit. The best fitting CAR Models are identified using the AIC, which is the standard output from this package. For the purposes of this paper, we can compare the DIC and AIC across models. The DIC can be a generalization of AIC under the special case where the Maximum Likelihood (ML) estimate coincides with the posterior mean (Berg, Meyer, & Yu, 2004). Since we use uninformative priors in our R-INLA Bayesian models, the priors are flat and the ML estimates correspond to the posterior mean. The AIC results from the frequentist analysis are then comparable to the DIC.

2.5 Results

The analysis was done for the Fall and Spring seasons separately. The results are consistent between both seasons. We first did a summary of the observed data. The weighted average catch per tow of flounder (ALB units) in 108 administrative regions over 24 years range during the Spring season, from a low of 0 to a high of 14, with a mean and standard deviation of 0.49 and 1.26 respectively. The cross correlation among the covariates, bottom

temperature, surface temperature, bottom salinity are summarized in Table 2.2.

A total of nine models were run on the Fall and Spring summer flounder data, using different subsets of the relevant covariates (See Table 2.1). We present results of the lowest DIC values. Model 8 and 9 are excluded, given their DIC values are much higher. The spatial-temporal model with lowest DIC is chosen. The results of all the models are summarized in Table 2.3. For each model an AIC or a DIC value was obtained depending on the package. Given that we can make the assumption that AIC and DIC are equivalent for our models, all model information criteria will be represented as DIC values.

Before identifying the best fitting spatial-temporal model, we first justify inclusion of specific parameters. Based on our understanding of the literature, we know that ocean temperature is an important covariate, however, it is not clear whether sea surface temperature (SST) or bottom temperature (BT) is the better explanatory variable. From the results we see that bottom temperature has a higher coefficient, although in the linear model both SST and BT are statistically significant at 1% confidence level. Given that bottom temperature and surface temperature are correlated, we eventually used the coefficient that was most stable across all models. We also tested for the significance of latitude and longitude. Both x, and y coordinates are statistically significant at 1% confidence level, justifying the need to account for spatial auto-correlation. In addition, Model 1 performs better with the inclusion of the $t-1$ lagged covariates, indicating the presence of a temporal effect. The models in the *spdep* package can be used to account for spatial autocorrelation as specified by Cressie (1993). Model 2 is the CAR Model from the *spdep* package. A limitation of the *spdep* CAR model as it is implemented in R, is that it cannot be run across a time series or for multiple years. Therefore, to allow some comparison, we show the results for a more recent year, and test for spatial autocorrelation. Similar to the linear model, adding lagged variables for BT and bottom salinity (BS) improve the model AIC. For Model 2 the bottom

temperature effect is around 3%, that is, an increase of 1 unit °C in the ocean bottom temperature is associated with a $3\% = \exp(0.03)$ increase in the incidence of summer flounder (area weighted-ALB units), and an increase of 1 unit parts per thousand[1] (ppt) of salinity with an increase of around $0.94\% = \exp(-0.05)$ in the incidence of summer flounder in (area weighted-ALB units).

As mentioned earlier, in the CAR models, a common border based neighborhood approach was used. For each model an AIC or a DIC value was obtained. The neighborhood matrix of the BYM-CAR models is identical in the *spdep* and R-INLA implementation. We also chose the R-INLA implementation as Gaussian distribution to be consistent with *spdep*. We should expect to get similar coefficients for similar years. We pick a few years to see how they would compare. The *spdep* BYM-CAR for year 2014 has $\beta_1 = 0.112$ for BT with 95%confidence interval $0.0359, 0.1875$, and $\beta_2 = -0.015$ for BS with 95%confidence interval, $-0.0385, .0686$. The results for the R-INLA BYM model for year 2014, vary slightly, with $\beta_1 = 1.2413$ and confidence intervals $0.0869, 2.3937$, and $\beta_2 = 0.39$ and confidence intervals -0.4. However, the results for the SST in both models is considerably closer. See Table 2.5. Inconsistency in the results indicates that the BYM-CAR models across *spdep* and R-INLA packages are not comparable and that careful model specification needs to be carried out to ensure all assumptions are consistent.

The R-INLA models are compared using the DIC value. We explored complex space-time models with interaction effects of structured space and time variations. The more complex models have a higher DIC. From Table 2.3 we identify Model 4 (as described in Table 2.1) to be the best based on the DIC value of 592.4 for the Fall data and DIC value 728.3 for the Spring data. The fixed effects $(\alpha, \beta_1, \beta_2...)$, can be exponentiated and interpreted as relative

[1]Salinity is the measure of all the salts dissolved in water. Salinity is measured in parts per thousand (ppt). The average ocean salinity is 35ppt. This is interpreted as, every kilogram (1000 grams) of seawater there is 35 grams of salt.

incidences of weighted fish presence in ALB units. Model 4, has β_1, bottom temperature and β_2, bottom salinity as the fixed effects. Based on the results in Model 4, during the Fall season, an increase of 1 unit °C in BT is associated with an increase of approximately 61%, that is exp(0.615) in the incidence of log (summer flounder) in (area weighted-ALB units).

Overall for the Fall we see that effect size of BT ranges from $7 - 60\%$ across models. The effect size of BS ranges from a decline in log abundance of $1 - 13\%$ across models. The DIC of the more complex models increases, however, the effect size remains stable within the said range. (Table 2.3). For the Spring Season, SST has a higher effect size, ranging from $8 - 38\%$ incidence in log (summer flounder) in (area weighted-ALB units) (See Table 2.4).

Table 2.2: Correlation matrix of covariates (Fall and Spring)

Variable	BS	BT	D	SST
BS	1.00			
BT	-0.33	1.00		
D	-0.69	0.27	1.00	
SST	-0.31	0.77	0.40	1.00

We predict different Fall temperature regimes (based on the bottom temperature distribution quartiles) uniformly over the entire Mid-Atlantic Bight region. As expected, the mean population predicted under the higher temperature regime is $5\% = \exp(0.05)$ units higher than the mean temperature regime (See Figure 2.6).

The predicted posterior mean for the model with the lowest DIC is plotted against time (Figure 2.9). We get a good visual representation of Model 6 and how it performs with respect to the area-weighted mean summer flounder abundance.

Finally, we also wanted to see how well Model 6 performs in predicting the abundance of summer flounder out of sample. The first modification in Model 6 has an inclusion of year

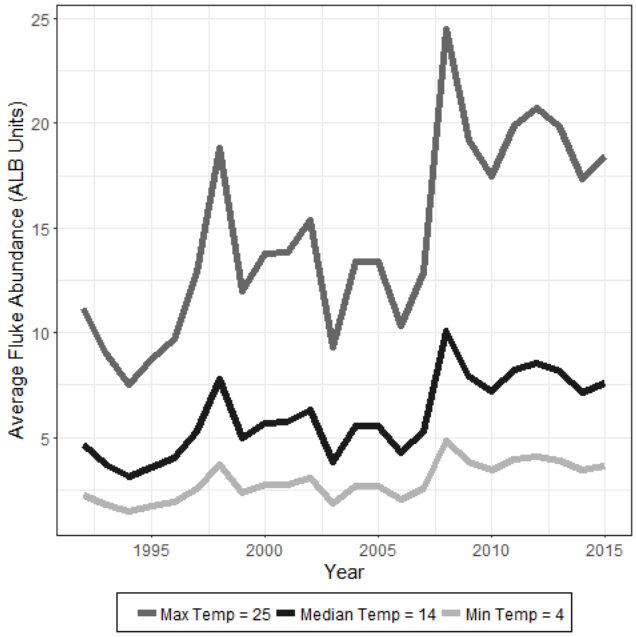


Figure 2.6: Simulating different Fall temperature regimes, assuming uniform temperature in the Mid Atlantic Bight, USA. Zero Inflated Poisson Model 6

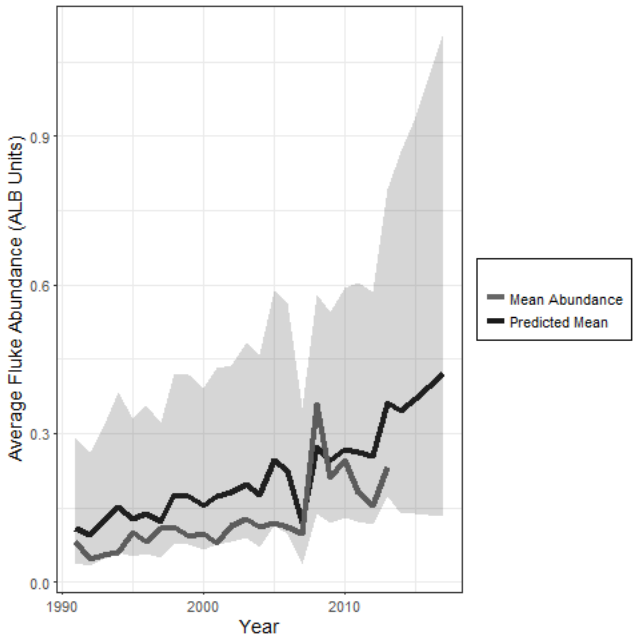


Figure 2.7: Predicting summer flounder abundance in Fall (blue line) with Year as Random Walk and rise in SST at 0.23 °C / year. Shaded area is 95% credibility intervals. Actual abundance (black line)

Model	Intercept	BT	SST	BS	BT^2	SST^2	Depth	Year	DIC
Model 3	-3.6167	0.3195		-0.0593	-0.0087			0.0507	600.2
Model 3	0.8719		0.1071	0.0124		0.004		0.0132	600.2
Model 4	-2.9567	0.315		-0.0583	-0.0085				596.5
Model 4	0.8669		0.1063	0.0124		0.004	0.0107		598.1
Model 4	**-6.4697**	**0.615**	**0.1005**	**-0.1368**	**-0.017**	**-2e-04**	**-0.0338**		**592.4**
Model 5	-4.8629	0.0813		-0.0156			-0.064		596.9
Model 5	0.7273		0.0289	0.0126			0.0111		600.4
Model 6	-2.7659		0.0552	-0.0039					590.3
Model 6	-5.5335	0.0739	0.0665	-0.0125			-0.0508		597.6
Model 6	-5.1474	1.0462	0.1361	-0.2216	-0.0328	0	-0.0136		619.3
Model 7	-0.2182	-0.0048		-0.0025					697.8
Model 7	-0.2016		-0.0073	-0.0028					690.9

Table 2.3: Results: Relevant parameter estimates with DIC - Fall Data

Model	Intercept	BT	SST	BS	BT^2	SST^2	Depth	Year	DIC
Model 3	-9.1579	0.1448		0.1754	-0.0115		0.0073	0.073	742.1
Model 3	-8.5014		0.3579	0.1114		-0.0129	0.0059	0.062	731.6
Model 4	-8.866	0.1589		0.1974	-0.013		0.008		740.3
Model 4	**-7.6373**		**0.3587**	**0.1102**		**-0.0129**	**0.0067**		**728.3**
Model 5	-13.3641	0.1623		0.3322	-0.013		0.0029		750.2
Model 5	3.8992		0.0833	0.1223		0.0031	0.0041		741
Model 6	-13.4921	0.1629		0.3363	-0.013		0.003		750.6
Model 6	-10.5578		0.3818	0.2063		-0.0138	0.002		741.1
Model 7	0.1311	0.0197		0.0043	0.0017		0.0011		833.2
Model 7	-0.1586		-0.0097	-0.0066		-7e-04	5e-04		832.2

Table 2.4: Results: Relevant parameter estimates - DIC - Spring Data

as the Random Walk (RW) component. The second version of Model 6 has year as a fixed effect factor variable. Both these models are used to predict summer flounder abundance out of sample for the years 2015-2020. The objective is to (1) see the linkage with temperature increase (2) compare credibility intervals using the two different approaches, namely with year as RW and year as fixed effect. The two versions of Model 6 are therefore used to

Parameters	*spdep* CAR	*spdep* CAR	R-INLA CAR	R-INLA CAR
Intercept	-0.646	-2.194	-22.5209	-13.326
	-2.5407 1.2481	-5.3105 0.9225	-55.0526 9.9616	-35.3989 8.7149
BT	0.112		1.2413	
	0.0359 0.1875		0.0869 2.3937	
SST		0.059		0.0805
		-0.2125 0.3309		-0.2675 0.4279
BS	0.015	0.065	0.3932	0.4152
	-0.0385 0.0686	0.0213 0.1093	-0.4929 1.2779	-0.2651 1.0945
BT^2	-0.004		-0.0349	
	-0.0066 -0.0018		-0.0667 -0.0032	
SST^2		-0.002		-0.0023
		-0.0084 0.0052		-0.0174 0.0129
DIC	33.17	47.48	-179.64	-180.58

Table 2.5: Results: Comparison of R-INLA and *SPDEP* packages BYM Model for Fall 2013. (Reporting β coefficients and confidence intervals)

predict the Fall abundance under a rising temperature regime of 2.3°C/ year [2] (See Figure 2.7). The model with the Random Walk (RW) performs better, however, the credibility intervals increase progressively out of sample. We observe that when predicting out of sample, credibility intervals increase progressively. However, when we removed the RW component and replace it with year as a fixed effect factor variable, we see the effect of temperature is more prominent, and the credibility intervals are narrower compared to the RW model (See Figure 2.8).

[2]Similar to the rate of ocean temperature increase used by Pershing et al. (2015)

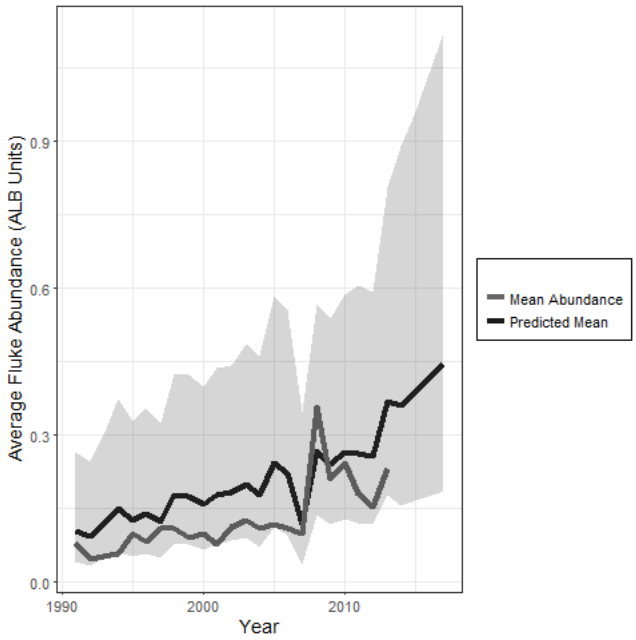


Figure 2.8: Predicting summer flounder abundance in Fall (blue line) with Year as fixed effect Factor and rise in SST at 0.23 °C / year. Shaded area is 95% credibility intervals. Actual Abundance (black line)

2.6 Discussion

The aim of this study was to develop methods for better understanding the relationship between ecologically significant physical oceanographic parameters (such as ocean temperature, bottom salinity, and bathymetry) while accounting for the spatial and temporal changes in abundance of summer flounder. Different spatial and spatial temporal models were explored.

The analysis focusses mainly on the Fall survey data, however, we also looked at the Spring bottom trawl data. Overall the results suggest that BT, SST, and BS are important covariates that explain the presence of summer flounder. The effect size of BT is twice that of SST in the Fall, indicating that during the Fall, BT has a bigger effect size. In the Spring season, the SST has a higher effect size. BS is an important covariate during both seasons. The results of applying the CAR, ZIP, and ZIP spatial temporal models, overall are also

consistent with our biological knowledge of summer flounder. From the results we can see that bottom temperature and SST are both significant determinants of summer flounder abundance. The effect size varies across models, ranging from $7 - 60\%$ for the bottom temperature and $8 - 38\%$ for SST. This result is consistent with previous studies that have examined the relationship between summer flounder abundance and temperature, where temperature is positively correlated with growth (H. R. Colburn et al., 2009; Grimes et al., 1989; Sackett et al., 2007). Not surprisingly, surface temperature and bottom temperature are collinear (Pearson correlation coefficient 0.76), therefore both are best represented when modeled separately during the Spring season. Intuitively, we should include at least one of the two covariates into our models. However, when both BT and SST are included in the model for the Fall season data, the model with the lowest DIC, includes both, with β coefficient values BT (0.615), SST (0.100), and BS (-0.13). Our results reveal that the abundance is correlated with sea surface temperature increase, although bottom temperature has a larger effect size in the Fall.

An interesting insight from the analysis of ocean temperature is that during Spring, the SST has a higher effect size on summer flounder. Our Spring results are therefore, consistent with the physical oceanographic mechanism whereby, the winter SST sets the BT, and hence also is more important in driving the distribution of summer flounder. In addition, summer flounder is a bottom dwelling fish, therefore, the winter SST is a good proxy for the Fall bottom temperature, given that bottom temperatures are set based on the lowest winter temperature. We can also conclude that satellite derived Spring surface temperatures can be a sufficient alternative to Fall bottom trawl measured bottom temperature.

However, we should also take into consideration the effect of SST in the Fall season, given that summer flounder spends a considerable time in estuaries. Therefore, increasing SST may have a stronger relationship with larval growth and survival rates as well.

Based on historical trends, we know that Winter and Spring bottom temperatures are not rising at the same rate as sea surface temperatures (See Figure 2.5). Therefore, we should not erroneously assume that the rates of increase in summer flounder abundance will follow the same upward trends that we are observing in Fall sea surface temperature. However, assuming all else constant, beyond certain bottom temperature thresholds, we can expect to see changes in abundance that will correspond to rising sea surface temperatures.

From a fisheries standpoint, given that Fall SST is changing more rapidly compared to BT, in the interim we will notice more dramatic impacts of SST increase on surface dwelling fish species. Although a precautionary approach should give consideration towards including the long term impacts of temperature on surface and bottom dwelling species in future stock assessments.

Similarly, the growth rates of larval stage are also associated with an increase in salinity (J. Burke et al., 1991; Rogers & Van Den Avyle, 1983). The coefficient on bottom salinity ranges from a decrease in $33 - 22\%$. These results are consist over both seasons.

In the *spdep* CAR models, ocean depth is significant in predicting the presence of summer flounder, although the effect size gets very small in the spatial models. Further studies are needed to determine whether deeper waters in the Gulf of Maine may act as a biological barrier for the summer flounder to migrate or survive..

Under the current temperature regime, another biological constraint in the Gulf of Maine is the availability of essential spawning habitat. The summer flounder migrates to on-shore breeding grounds in the estuaries areas of Pamlico Sound and Chesapeake Bay (Packer et al., n.d.). The summer flounder is a winter shelf-spawning species, using the same spawning grounds and wintering areas each year (Wilk et al., 1980). Therefore a shift from an essential spawning habitat present in the Mid-Atlantic Bight to the shores of the Gulf of Maine has

currently not been observed. Movement of the summer flounder may be restricted near the essential spawning habitat near the estuaries, although in the early fall summer flounder migrate offshore towards the outer continental shelf at depths of $150m$ (Terceiro, 2006). However, Able et al. (2010) argue that with warming ocean temperature estuaries in the northern range will become suitable habitat for the summer flounder, resulting in higher recruitment and most likely an increase in stock abundance (Able et al., 2010). When we account for temperature increase and project summer flounder abundance, our models do predict an increase in summer flounder incidence.

The second objective of this research was to explore alternative models, and test how various assumptions in each model resulted in different estimates of the size effect of temperature. We explored this problem using the Conditional Autoregressive Model in the *spdep* package (Bivand, 2007) and the R-INLA models in the R-INLA package (Blangiardo & Cameletti, 2015). One of the limitations in the *spdep* package is that the data must be approximated by a Gaussian distribution. In an alternative package, CARBayes, the response data can follow binomial, Gaussian or Poisson distributions (Lee, 2013). However, the models in CARBayes are set according to the Bayesian framework based on an MCMC simulation. We did not fit our data to the more computationally intensive CARBayes models in this paper.

Further, we were unable to include a temporal component in our conditional autoregressive models within the *spdep* package. Even if we use the same assumptions to build a neighborhood structure that is comparable to the R-INLA package, the *spdep* CAR will only run the model one-year at a time. The temporal autoregressive component gets captured in the error variance. The second constraint is that we must use a Gaussian distribution, which doesn't account for over-dispersion of our observations. The initial use of the linear regression and *spdep* CAR models is therefore relevant in giving insight regarding relevant covariates, and identifying non-linearities, and spatial dependencies in the data.

Our data is characterized by the Zero-Inflated Poisson model with BYM-CAR random effect specifications (Besag et al., 1991) and temporal autoregressive random effects. The R-INLA models have the additional flexibility to allow for distributions that better represents our data. The best fitting R-INLA Model, Model 4 separately identified spatial and temporal components. The most complex R-INLA model resulted in spatially and temporally structured random effects, however, the DIC was much higher for the complex space-time interaction model-the DIC which comprises of a component that measures model fit, and another component that measures model complexity through the effective number of parameters. The more complex models also perform poorly in fitting the average abundance and trend, therefore when we fit the predicted abundance to the actual abundance, the models with the lower DIC perform better (See Figure 2.9 for Model 6). Therefore, one of the main findings is that the more complex models tend to over parameterize the system, which reduce the effect size of explanatory variables.

Biologically one would expect fish abundance to be spatially and temporally autocorrelated. The approach that is included in the R-INLA models account for spatial and temporal effects, spatial temporal interaction effects. The spatial correlation is accounted for in the conditional autoregressive models, with a random walk component in the temporal time-trend. The draw-back with these more complex models is that they tended to over-parameterize the system, and reduced the effect size of bottom temperature. It is likely that this is because more complex models increase the chances of collinearity between covariates of interest. For example, the inclusion of random variables for the interaction of spatial and temporal effects may be correlated with BS, BT or SST, therefore including the structured temporal component in the model may give a mis-leading result. Beyond identifying the effect size, the models are used to make future predictions. The inclusion of appropriate random effects such as the temporal effect is useful. The structured year effect seen as a

stochastic process better represents the system that we are trying to model. It is appropriate because it characterizes the kind of uncertainty that we expect to see across years. Another objective could have been to study specific year-effects. In that case, we would choose year to be a fixed effect as opposed to predicting an overall random effect. The credibility intervals for fixed effects, therefore tend to be less wide, representing a narrower variance, whereas random effects represent broader variances that encapsulate the temperature variation and result in wider credibility intervals when predicting beyond the data (See Figure 2.7 and Figure 2.8 for a comparison of variance estimates).

With respect to the first objective, there are some notable limitations of this study. We only consider a restricted subset of environmental covariates. Warming oceans, fishing effort and changing Atlantic Multi-decadal Oscillations (AMO) are the known drivers of change in the summer flounder abundance and distribution, even though the exact mechanisms behind these drivers are not understood in entirety. Recent research on spatial temporal models has demonstrated that fishing effort is an important determinant in understanding the growth and movement of fisheries (Thorson et al., 2016). We do not incorporate space-time covariates for fishing effort. The summer flounder is vulnerable to fishing pressure, given its behavioral traits such as spawning aggregations, site fidelity, segregation by sex, migratory bottlenecks, and the unusual attraction to gear (MAFMC, 1998). Without the space-time information on fishing effort, it is difficult to conclude empirically if spatial and temporal variation is a determinant of fishing effort. Bell et al. (2015) conclude that fishing mortality in the early 1980s and 1990s was negatively correlated with summer flounder abundance and exhibited no link with temperature. Bell et al. (2015) also concluded that linkage with temperature would become more pronounced after 2009. Including fishing effort in our models is an area for future research. It is important to acknowledge that the coefficients on bottom temperature are relatively stable across the different spatial temporal models.

Therefore, we anticipate that the results from the inclusion/exclusion of other significant parameters of interest will not alter the coefficient on bottom temperature.

While individual stressors, such as rising salinity (J. Burke et al., 1991; Rogers & Van Den Avyle, 1983), temperature (H. R. Colburn et al., 2009; Grimes et al., 1989; Sackett et al., 2007), and fishing pressure (Bell et al., 2015) have been linked to species abundance, the interaction effects of temperature and AMO with other climate change induced stressors are still not fully understood (Blackford, 2010). Fishing pressure by statistical region can be used to investigate the interacting effects of spatial and temporal variation in fishing pressure and abundance.

Having established that temperature (BT during Fall and SST during Spring) is an important covariate, we can anticipate that with rapid changes in key environmental variables, there will be larger variations in the spatial and temporal distribution of summer flounder as environmental variables change. Further research is needed to explore whether the summer flounder range is expanding, and whether there are any interaction effects of fishing effort and temperature increase. Understanding the implications of these effects on the abundance and spatial trend of the summer flounder has important management implications. Expansion of species range may cause trip lengths to increase for some fishermen, which implies increased cost (harvester time, fuel, man-hours). It may result in shifting opportunities to harvest other species, result in more harvesters entering the fishery, or exiting the fishery. Understanding spatial and temporal trends of summer flounder have implications for management. Management can then be better prepared to adapt to the changing fishery dynamic (L. L. Colburn et al., 2016).

Summer flounder is an economically important flatfish, therefore the threats associated with potential future climate regime shifts and increased stochasticity should cause managers

to adopt a more precautionary approach by maintaining higher resource stock levels (Polasky, de Zeeuw, & Wagener, 2011), as opposed to increasing quotas and shares across states in response to rising stock abundance. In addition to regulating quotas, fishery managers should also take into consideration the impacts of watershed management on this commercially and economically viable fish species.

Summer flounder habitat includes pelagic waters, demersal waters, salt-marsh creeks, sea grass beds, mudflats, and open bay areas from the Gulf of Maine through North Carolina. Therefore the species interacts with different temperature regimes during the course of its life-cycle. This can be one of the reasons why both SST and BT are important covariates explaining abundance. For future research, these model outputs can be modified to test if the summer flounder abundance will rise in the Gulf of Maine, given rising temperature and salinity regimes. The spatial models developed in this study can be used to test similar region specific hypothesis from previous studies (Bell et al., 2014; Lavelle, 2014).

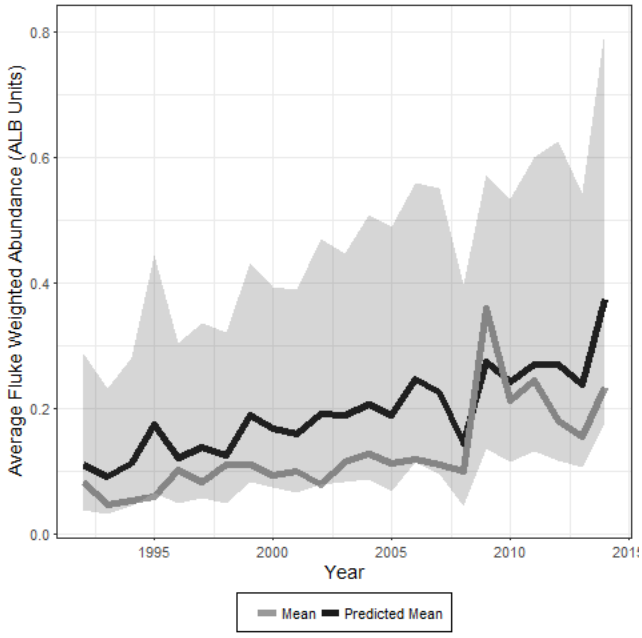


Figure 2.9: Zero Inflated Poisson Model 4 in R-INLA (Fall Data) with β coefficients SST and BT

2.7 Conclusion

The objective of this research was to identify the main ecological determinants of summer flounder. Overall, in our analysis we find that bottom ocean temperature, sea surface temperature and bottom salinity are the most important predictors of summer flounder. The main questions that we attempted to address were (1) what are the ecological determinants of the spatial-temporal distribution of summer flounder; and (2) Which spatial models can best be used to characterize our data. Our results reveal that the effect size of temperature is biologically relevant for explaining the spatial variation in summer flounder abundance in the Mid-Atlantic Bight. Fishing effort is an important covariate that should be included in future research. We can assume that in our models temperature captures the effect of fishing effort, and that the temporal autoregressive random effect captures the temporal trends. For the second objective, we identified the best fitting spatial models. The *spdep* CAR models account for spatial autocorrelation with the BYM specification, however, these models cannot account for over-dispersion. Our dataset is comprised of zero-inflated count data characterized by the Poisson distribution. Therefore we can expect to see over-dispersion in the estimates. The Zero-Inflated Poisson Models implemented in the R-INLA package performed better. In addition to the BYM and BESAG specifications in the intrinsic CAR, the spatial temporal interaction models where able to better account for the interaction through the random effects ν_i and γ_t. Where ν_i represented the unstructured spatial effect, γ_t the structured temporal effect. One trade off that we notice between the more complex models and the simpler ZIP models is that, the estimate of the coefficients degrade and uncertainty increases as the models become more complex. Future research can use simulation exercises to determine whether the more complex models are over parameterizing the system. Overall this exercise has given us considerable insight into predicting spatial and temporal distribution of summer flounder under different ocean temperature and salinity regimes.

CHAPTER 3

PURE OPEN ACCESS AND SPATIAL MANAGEMENT IN A TWO-ZONE FISHERY

UNDERSTANDING THE EFFECT OF CLIMATE CHANGE ON FISHERIES AND FISHING COMMUNITIES: A THEORETICAL AND AN EMPIRICAL APPROACH

Samar Deen, Ph.D.

Cornell University 2017

In 1994, the State of Maine partitioned the green sea urchin fishery into two zones. This was justified on the basis of different spawning times. The green sea urchin in the western zone (Zone 1) spawns earlier than urchins in the eastern zone (Zone 2). High prices for urchin roe induced high levels of fishing effort and resulted in a precipitous decline in urchin biomass, particularly in Zone 1, which by 2005 had reached the zero profit condition symptomatic of a pure open access equilibrium. We develop three models to understand the dynamics in the Maine green sea urchin fishery. The first model is a two-zone, pure-open-access (2ZPOA) model calibrated to the bionomic conditions in the Maine green sea urchin fishery, *circa* 1995. The 2ZPOA model is capable of complex dynamic behavior which we explore via simulation and the calculation of eigenvalues for the four by four Jacobian matrix evaluated at the two 2ZPOA equilibria. The second model 2ZPOA Non Stationary Non Steady State Model permits effort to vary overtime in both Zones to minimize the objective function such that the sum of square difference between the model and Hunter's (2015) biomass effort. Finally we optimize values of effort to improve the current net revenue values in the fishery through a counter-factual optimization model. All three models give us different perspectives on how we can understand changing dynamics in a fishery, especially for slow-changing variables.

3.1 Introduction

Gordon (1954) developed a static model to explain why a competitive industry, harvesting a common property fishery, would typically reach a zero-profit equilibrium, where the fish stock was typically reduced to a fraction of its pre-exploitation level. Garrett Hardin's more famous article, *The Tragedy of the Commons*, published in *Science* in 1968, reached a similar conclusion, describing the incentive of pastoralists to over-graze the commons in 18th century England. V. L. Smith (1968, 1969) developed dynamic models of production from natural resources and the open access harvest of a common property fishery. Clark (1976) reviewed both the static and dynamic versions of what is now referred to as the *pure open access model*, calling the zero-profit equilibrium the *bionomic equilibrium*, since the equilibrium fish stock and level of fishing effort depended on parameters from the biological growth function, the production function, the dockside price for fish, and the unit cost of fishing effort.

The economic history of fishing, whaling, and sealing provides empirical support for the predictive power of the pure open access model. Wilen (1976) estimates a pure open access model for the North Pacific fur seal. Bjorndal and Conrad (1987) develop a dynamic open access model for the North Sea herring fishery, while Amundsen, Bjørndal, and Conrad (1995) examine the dynamics of the minke whale in the Northeast Atlantic, which was harvested under open access conditions until the end of the 1970s. J. M. Conrad (2005) uses a pure open access model with critical depensatory growth to explore the dynamics leading to the extinction of the passenger pigeon.

While the pure open access model has undisputed historical relevance, Homans and Wilen (1997) have argued that many contemporary fisheries are now managed using a total allowable catch, or TAC. Fishing is allowed until the aggregate catch by competitive fishers reaches the TAC, at which point the season is closed. Homans and Wilen (1997) refer to

this management system as *regulated open access*. The Pacific halibut fishery, in the Gulf Alaska, provided an ideal empirical study prior to the adoption of individual transferable quotas (ITQs) in 1995. An open-access fishery managed with a TAC results in "a race for the fish," leading to a compressed fishing season, large harvests during a short period of time, freezing of fish which would have fetched a higher price if sold fresh (during a longer fishing season), and fishers overloading vessels with the increased risk of capsizing in foul weather.

Beginning in the 1990s, resource economists started developing spatial bioeconomic models in recognition of the fact that resource abundance changes over both time and space and that the location of a resource is important to explaining the behavior of fishers and the formation of optimal spatial-management policies. The early spatial literature was developed in part to evaluate the potential benefit of "no fish zones" or marine reserves. Brown and Roughgarden (1997) analyzed a two-zone meta-population where diffusion from one area might significantly increase the density of biomass in the other area. This "non-convexity" can make it optimal to designate the source area as a marine reserve while restricting fishing to the receiving (sink) area. J. Conrad (1999) developed a two-zone, stochastic model where diffusion between zones was density dependent. There were no non-convexities in Conrad's model, but the creation of a marine reserve had the potential to reduce the overall variability in biomass in the zone where fishing was allowed.

Sanchirico and Wilen (2005) examined optimal spatial management in an n-patch system by introducing patch-specific effort or landings taxes. Optimal taxes will vary over time and space as biomass, and thus patch-specific shadow prices, change. Costello and Polasky (2008) developed a multi-patch stochastic model based on Reed's (1979) model of a fishery with stochastic growth. Optimal escapement, S^*, was constant in Reed's model with harvest being zero ($Y_t = 0$) if biomass was less than or equal to optimal escapement ($X_t \leq S^*$) or

equal to the excess of biomass over optimal escapement ($Y_t = X_t - S^*$) if biomass exceeded optimal escapement ($X_t > S^*$). With stochastic growth, patches might be opened or closed to fishing in a given year. Permanent closure would be optimal if biomass in a patch never exceeded its optimal escapement.

In this article, we develop a two-zone-pure-open-access (2ZPOA) model and apply it to the green sea urchin fishery in the State of Maine. The two zones are biologically connected because larvae from Zone 2 may diffuse and settle in Zone 1. The dynamics of this discrete-time, two-zone system can be complex, with bionomic equilibria being stable or unstable. We conduct sensitivity analysis on effort adjustment parameters and show how the 2ZPOA equilibrium might change from stable spirals to stable limit cycles.

We then ask if periodic closure of one or both zones might be optimal to allow stocks to rebuild and whether creation of a marine reserve would be optimal. We develop a mix-integer optimization model where zone-specific mortality rates (ω_i, $i = 1, 2$) and binary variables, $B_{i,t}$ are chosen to maximize the present value of net revenue. Specifically, $B_{i,t} = 0$ if zone i is closed in year t, and $B_{i,t} = 1$ if zone i is open in year t. When fishing is allowed in Zone i, $1 > \omega_i > 0$ is the rate of fishing mortality. We pose and solve the mixed-integer optimization problem for the Maine green sea urchin fishery when the model is calibrated to the bionomic conditions, *circa* 1995.

The rest of this article is organized as follows. In the next section we describe the biology of the green sea urchin in coastal Maine. In Section 3, the brief, boom-bust, history of the commercial fishery is chronicled. In Section 4 we present the 2ZPOA model, identify the two bionomic equilibria, and determine their local stability. In Section 5 we present an open access non stationary non steady state model where E, the effort is permitted to vary. In Section 6 we pose the mixed-integer optimization problem and solve for effort

values that maximize the present value of net revenue. Section 7 provides a discussion of the results from the three models and the main motivation behind assessing the differences between the steady state and dynamic systems. This section also develops, in general form, a more complex, multi-species model. The multi-species model is motivated by the suspicion that the Maine coastal ecosystem may in fact support two stable steady states; one with high urchin biomass and low biomass for kelp and crab, and the other with low biomass for urchin and high biomass for kelp and crab. Over-harvest of urchins in the 1990s may have "flipped" (Harris & Tyrrell, 2001; Steneck et al., 2002; Steneck, Leland, Mcnaught, & Vavrinec, 2013) the ecosystem into the basin of attraction for this second, economically less desirable, equilibrium.

3.2 Biology of the Green Sea Urchin

Spawning in the western zone (Zone 1) begins in late February or early March, extending over a period of 60 days when the waters warm to $5 - 6°$C. In the Eastern Maine (Zone 2) spawning begins in early April and extends into May ($34 - 50$ days) as waters warm to $4 - 5°$C. The changes in gonad indices are synchronous between male and females and the spawning events are correlated with an increase in phytoplankton chlorophyll-a as well as increased water temperature (Himmelman, 1978; Siikavuopio et al., 2012, 2008). There is spatial and temporal variability in spawning and growth rates of the green sea urchin in both zones as noted by Russell (2000); Russell, Ebert, and Petraitis (1998); Vadas, Beal, Dudgeon, and Wright (2015). The percentage of eggs fertilized varies between 50% to 85% depending on oscillatory currents but can decline to below 10% under turbulent conditions (Kregting, Bass, Guadayol, Yund, & Thomas, 2013). Fertilized sea urchin larvae begin feeding after $2-3$ weeks and remain pelagic for slightly over 50 days before metamorphosing

and settling Strathmann (1978). This suggests that the sea urchin's pelagic larval phase is highly dispersive (Ling, Johnson, Ridgway, Hobday, & Haddon, 2009; Strathmann, 1978). The long-lived planktotrophic larval phase also facilitates the dispersal of larvae from parental sites to suitable habitats (Ling et al., 2009). There are high mortality rates of larvae before settlement due to predation, starvation and extreme environmental conditions Seward (2002). Lower turbulence in the water increases the propensity (up to $50-90\%$) of larvae to settle and metamorphosize (Gaylord, Hodin, & Ferner, 2013). Urchin roe swells in fall and early winter, and is most valuable in late fall and winter, when it is ideally suited for the Japanese market (Vadas et al., 2015). The larvae display equal preference for dominant substrata of barrens and kelp beds, and differences in the density of larval settlement cannot be explained by the differences in adult densities (Rowley, 1989). Urchins sexually mature in their third year (diameter $2.5-3.8$cm), and at 8.0cm a female can produce up to 10 million eggs (T. R. Johnson, Wilson, Cleaver, & Vadas, 2012), with a fertilization rate of $50-90\%$ (Brady & Scheibling, 2006). Our pure open access model is based on the dynamics of adult, sexually mature biomass. A typical cycle for Strongylocentrotus droebachiensis in Maine (Figure 3.1) has stages, prematuration (fall development of roe contents and gonad growth), maturation (Winter), spawning and melt (Spring) and recovery (Summer) Vadas et al. (2015). The 2ZPOA model assumes that the spawning and growth in both zones occurs simultaneously, the spatial component accounts for the larval drift from Zone 2 and Zone 1, as part of the annual model.

No direct estimates for r (intrinsic growth rate) , K (carrying capacity), q (catchability coefficient), and $1-\alpha$ (dispersal) exist. We did an extensive review of the literature to get parameter estimates that are plausible and generate trajectories consistent with the stock estimates. A detailed summary of the sea urchin biological parameters are in Table 3.1.

The growth of the green sea urchin has been described using the von Bertalanffy growth

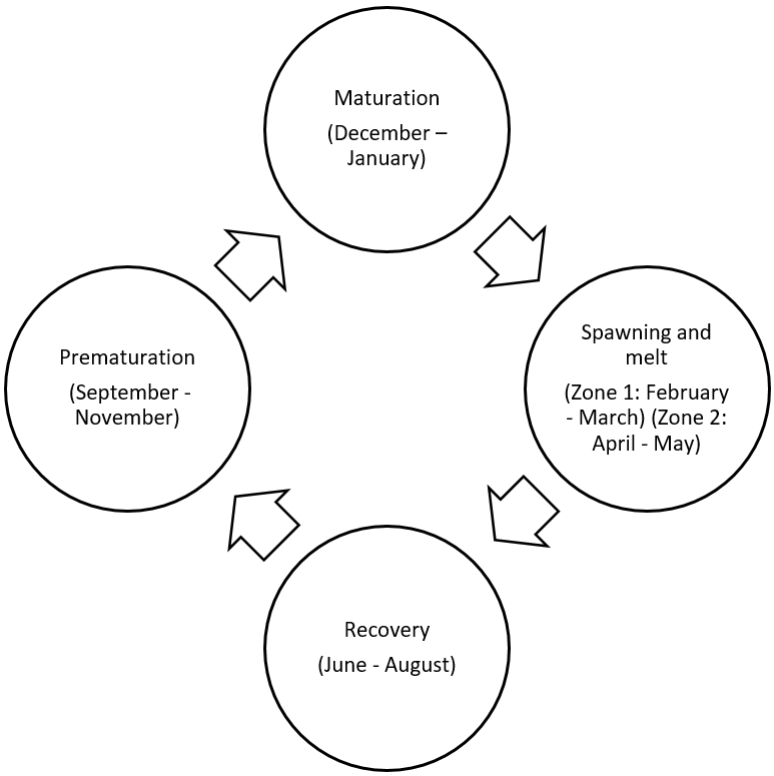


Figure 3.1: A typical cycle for Strongylocentrotus droebachiensis in Maine (Vadas, 2015)

curve (Munk, 1992). Pederson and Johnson (2008) examine how sea urchin growth rates vary between particular habitat types using the commonly applied generalized Richards function. Brady and Scheibling (2006) fit logistic growth curves to gonad index and test diameter size-at-age. M. D. Smith and Wilen (2004) develop a meta-population model representing 24 discrete size-structured populations linked by a dispersal matrix applying the von Bertalanffy equation.Kanaiwa, Chen, and Hunter (2005) apply a Bayesian stock assessment framework with a size-structured population dynamics model independent of spawning stock biomass using a simulation approach. Chen et al. (2003) develop a growth-transition matrix for the sea urchin stock with the objective of capturing the variations in growth increments among individuals, using the von Bertalanffy growth function to specific areas and habitats. See Table 1 in Chen et al. (2003) for a summary of the growth parameters used by Grabowski, Windholz, and Chen (2005).

Table 3.1: Parameter Estimates for the Maine Green Sea Urchin 2ZPOA Model

Symbol	Description	Value	Source
r_1	Intrinsic growth rate Zone 1	0.4	estimate derived from Zhang (2008)
r_2	Intrinsic growth rate Zone 2	0.6	estimate derived from Zhang (2008)
K_1	Carrying capacity Zone 1	31,877 (mt)	Hunter (2015)
K_2	Carrying capacity Zone 2	35,065 (mt)	Hunter (2015)
$X_{1,0}$	Initial condition in Zone 1	11,978 (mt)	Grabowski (2005)
$X_{2,0}$	Initial condition in Zone 2	18,312 (mt)	Grabowski (2005)
$E_{1,0}$	Initial Effort in Zone 1	36 (effort index)	estimate derived from NMFS port agent and dealer reports (See Appendix)
$E_{2,0}$	Initial Effort in Zone 2	43 (effort index)	estimate derived from NMFS port agent and dealer reports (See Appendix)
α	Diffusion Parameter for Larvae from Zone 2 to Zone 1	0.8	Assigned
S	Survival of larva Dispersed from Zone 2 to Zone 1	0.2	Assigned
p	Urchin price ($ per mt)	3500	Average Price from 1994-2013, NMFS Port Agents and Dealer Reports
η_1	Effort Adjustment Parameter, Zone 1	0.005	Assigned
η_2	Effort Adjustment Parameter, Zone 2	0.001	Assigned
c_1	Cost per Dive Hour, Zone 1	50,000 (dive dragger year)	Assigned
c_2	Cost per Dive Hour, Zone 2	75,000 (dive dragger year)	Assigned
q_1	Catchability, Zone 1	0.02	Estimated in Appendix
q_2	Catchability, Zone 2	0.07	Estimated in Appendix

The most recent stock assessment of the green sea urchin estimated the pre-1990s urchin population was closer to the carrying capacity of the urchin fishery, and that the *circa* 2003 stock was at 10% of the virgin carrying capacity (Chen et al., 2003; Harris & Tyrrell, 2001). This enables us to estimate a value of K that corresponds to a the hypothesized pre-1990s urchin population. We use an estimate of the intrinsic growth rate from the Tanaka and Logistic growth functions as shown in Figure 3 in Zhang, Campbell, and Bureau (2008).

Parameterizing the larval dispersal coefficient $(1-\alpha)$ is also challenging. Data related to settlement timing, differential settlement (Lambert & Harris, 2000) and the oceanographic patterns describing the Gulf of Maine gyre provide some insight about larval transport

within the Gulf of Maine, which is comprised of a counterclockwise gyre that traces the coast from Nova Scotia westward into the Gulf to Cape Cod and then an eastward jet along the inner edge of Georges Bank, with relatively lower accumulation of larva along the eastern coast, than along the western coast of the Gulf of Maine (Li, He, & Manning, 2014; Vermersch, Beardsley, & Brown, 1979). Our model focuses on the assumption that circulation in the Gulf of Maine gyre system transports larva southward into Zone 1, at which point they are transported back and redistributed into Zone 2. The dispersal coefficient will be parameterized to emulate the Gulf of Maine gyre system. The remaining parameters, S (survival rate), η_1, η_2, for which we were unable to find any relevant literature, are based on our best understanding of the fishery. Additional biological parameter estimates for the green sea urchin have been summarized in Appendix B.3, Table B.4.

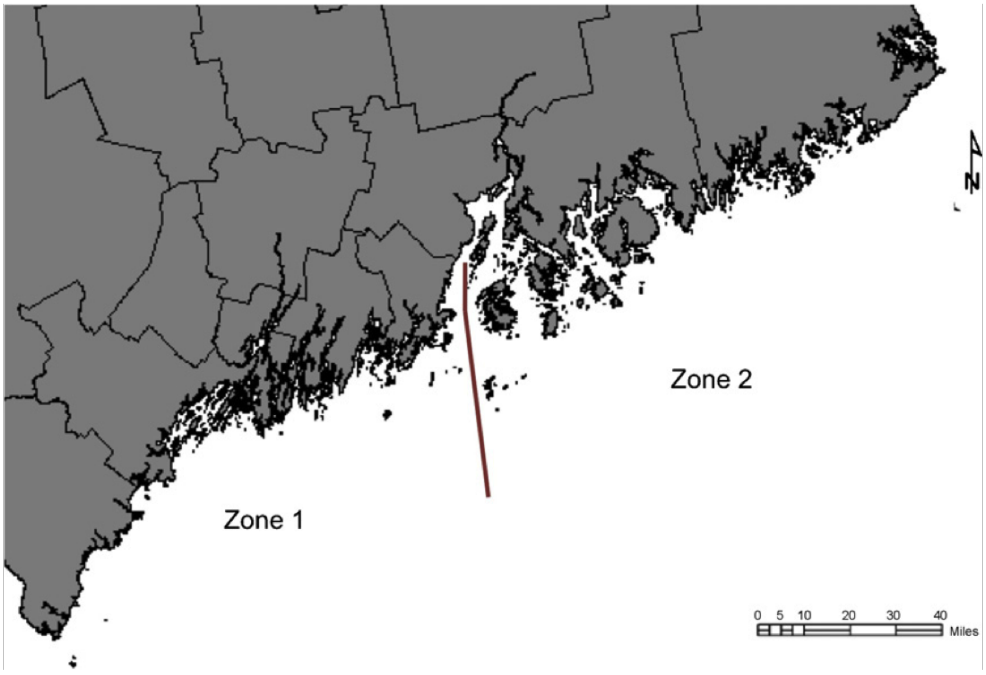


Figure 3.2: Map of the Sea Urchin Zone Council boundaries.

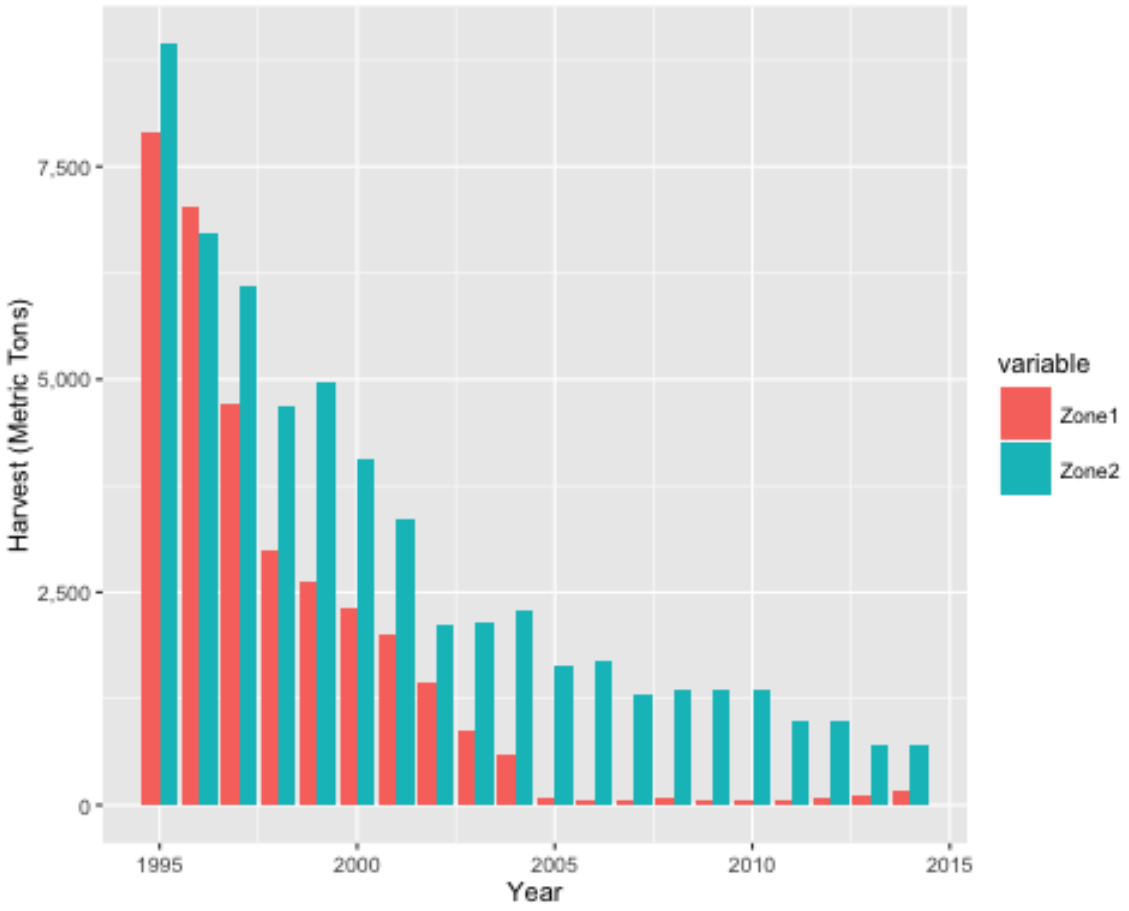


Figure 3.3: Green Sea Urchin Annual Harvest (1995-2014)

3.3 The Green Sea Urchin Fishery in Maine

In New England, coastal shellfish fisheries are managed either directly by the State or management is ceded to various local government institutions and town municipalities. In Maine, for example, the green sea urchin is managed by the Maine Department of Marine Resources (Mackenzie, 2008). In Massachusetts and other coastal states, the harvest limits of the bay scallop are governed by a state law, however, much of the management decision-making has been ceded to local towns and municipalities (Liu & Kritzer, 2013).

The green sea urchin fishery in Maine can best be described one that underwent a boom

followed by a bust, similar to the boom bust in the Japanese urchin fishery. In the 1970s there was a global decline in urchin abundance, starting with a rapid decline of up to 40% of urchin biomass in Japan. This resulted in the opening of the Japanese market to imports from Maine, where the quality of the roe was regarded as high quality by Japanese consumers. The boom in the Maine urchin fishery began in the 1980s and by 1987 the previously unexploited urchin fishery in Maine was valued at $1.7 million (Kiley, 2009). In the early 1990s, one license holder could earn up to $\$150,000$ during the 85-day season. Licenses were issued by the Department of Marine Resources (DMR) to monitor the number of urchin harvestors in the state but there was no limit on harvest. The state of Maine also created two fishing zones (Figure 3.2) (T. R. Johnson et al., 2013) to manage legal harvesting days when the fishery was open. The ecological basis for the two zones was justified by the difference in time of spawning along the coast (Vadas et al., 2015). In 1994 there were 3000 licensed divers and draggers in the fishery. By 1999 the green sea urchin fishery was the second largest fishery in Maine, after lobsters, valued at $30 million to harvesters (Chen et al., 2003). (See Figure 3.3). In 1994 the state placed a moratorium on licenses, allowable fishing days. Despite the creation of fishing zones and various seasonal closures in response to spawning dates, licenses and limited entry, there were no total or individual catch limits. Consequently, the urchin fishery was aggressively harvested and the stock was depleted to 90% of its initial biomass levels (*circa* $1998 - 2001$).

Similar to the biological parameter estimates, we rely on official landings reports, and previous literature to get economic estimates of the fishery (See Table 3.2), where $X_{1,t}(mt)$ denotes estimated biomass of adults in Zone i in year t, measured in metric tons (mt). These exploitable biomass estimates have been derived by a stochastic observation-error length-structured model in Chen et al. (2003) and Hunter (2015). The green sea urchin landings data has been provided by the Maine Department of Marine Resources. The dataset includes

an Urchin Survey from 2003-2015, with estimates of catch per unit effort (CPUE) and the average bottom hours for drivers in Zone 1 and Zone 2 for the years 1995-2013. The harvest data $Y_{i,t}$(mt) is based on the NMFS port agent and dealer reports. The annual counts of Maine commercial sea urchin licenses (Table B.1) for *circa* $1995 - 2013$ have been provided by the Maine Department of Marine Resources.

The effort data is derived from the bottom hours data for *circa* 1994-2009 provided Maine Sea Urchin Council from summary of the agent and dealer reports. Effort in the urchin fishery is disaggregated between divers and draggers. We also use the annual counts of Maine commercial sea urchin licenses owned by divers and draggers to estimate the aggregated effort by Year and Zone (See Appendix).

In the early 1990s, one license holder could earn up to $\$150,000$ during the 85-day season (Mack Kiley, 2009). Licenses were issued by the Department of Marine Resources (DMR) to monitor the number of urchin harvestors in the state but there was no limit on harvest. On average the annual cost to a fishermen is estimated to range to from $\$50,000 - \$75,000$. We consider the cost to be represented as a percentage of gross income obtained from landings of urchin from diving or dragging.

The catchability coefficient has been estimated by Chen et al. (2003) at $q = 0.014$ with the lower fifth percentile at $q = 0.009$. We estimate the catchability coefficient modeled on the Gordon-Schaeffer function using the available economic data (See Appendix). Our estimates for Zone 1 and Zone 2 of the catchability coefficient are consistent with other scientists' studies Chen et al. (2003). Based our knowledge of the economic parameters we identify the relevant parameters for our 2ZPOA model in Table 3.1. These parameter values are then used to simulate the biomass estimates of the 2ZPOA model in columns two and three for Zone 1 and Zone 2 respectively. Our model estimates the decline of the urchin fishery over

Table 3.2: Green Sea Urchin Fishery Economic Data

	Year	$X_{1,t}(mt)^a$	$X_{2,t}$ (mt)	$Y_{1,t}$ (metric tons)^b	$Y_{2,t}$ (hrs)	$Effort_{1,t}{}^c$	$Effort_{2,t}$	Price ($/$mt$)
1	1995	11978	18312.00	7021	6705.00	36.52	43.28	2412
2	1996	8339	15746.00	4805	6016.00	47.65	30.29	2451
3	1997	6038	13109.00	3138	4550.00	39.63	25.60	2380
4	1998	5152	11577.00	2765	4811.00	46.69	23.52	2647
5	1999	4502	9724.00	2385	3991.00	47.24	23.20	2951
6	2000	3719	8401.00	2148	3213.00	49.81	22.92	3000
7	2001	2223	5852.00	1524	2037.00	45.72	23.79	2723
8	2002	1305	5860.00	921	2118.00	42.65	26.25	2875
9	2003	716	5633.00	612	2261.00	28.59	25.76	3077
10	2004	280	5033.00	71	1647.00	22.78	23.93	3371
11	2005	307	4867.00	51	1697.00	15.70	21.87	3067
12	2006	361	4467.00	70	1304.00	10.18	21.31	3327
13	2007	421	4290.00	81	1350.00	10.59	19.69	3517
14	2008	446	3957.00	63	1343.00	8.18	19.87	3612
15	2009	498	3597.00	55	1357.00	6.94	18.24	4172
16	2010	526	3186.00	67	977.00	7.96	19.81	4916
17	2011	601	3121.00	82	975.00	4.51	20.79	4795
18	2012	697	2985.00	124	710.00	5.16	18.35	6847
19	2013	724	2983.00	174	698.00	6.09	17.64	5794

[a]Expolitable biomass estimates from Hunter (2015)
[b]Harvest levels, Maine Department of Marine Resources
[c]Derived index reflecting dive and dragger effort (See Appendix)

time, it does not address the multi-species dynamics in the urchin fishery (Kanaiwa et al., 2005; Steneck et al., 2013; Vavrinec, 2003).

3.4 The Two-Zone-Pure-Open-Access (2ZPOA) Model

The 2ZPOA model in discrete time consists of four coupled, nonlinear, first-order, difference equations. Each zone has two equations, one describing the dynamics of the urchin population and the other describing the dynamics of fishing effort. Urchin biomass will be measured in metric tons and effort will be measured in an index reflecting dive and dragger hours. The zones are biologically linked through the dispersion of larvae from Zone 2 to Zone 1. The four first-order difference equations take the form

$$X_{1,t+1} = (1 + r_1 - q_1 E_{1,t} - r_1 X_{1,t}/K_1)X_{1,t} + S(1-\alpha)[r_2 X_{2,t}(1 - X_{2,t}/K_2)]$$

$$X_{2,t+1} = (1 + \alpha r_2 - q_2 E_{2,t} - \alpha r_2 X_{2,t}/K_2)X_{2,t}$$

$$E_{1,t+1} = [1 + \eta_1(pq_1 X_{1,t} - c_1)]E_{1,t}$$

$$E_{2,t+1} = [1 + \eta_1(pq_2 X_{2,t} - c_2)]E_{2,t}$$

The first equation describes the dynamics of the urchin population as harvested in Zone 1. It assumes logistic net growth, $r_1 X_{1,t}(1 - X_{1,t}/K_1)$, where r_1 is the intrinsic growth rate and K_1 is the environmental carrying capacity. From logistic net growth we deduct harvest given by the Schaefer production function, $Y_{1,t} = q_1 X_{1,t} E_{1,t}$, where $Y_{1,t}$ is the level of harvest, also in metric tons, from Zone 1 in year t, $q_1 > 0$ is the catchability coefficient for Zone 1, $X_{1,t}$ is the harvestable (adult) biomass in Zone 1 in year t, and $E_{1,t}$ is the effort index for Zone 1 in year t. Zone 1 benefits from the diffusion of larvae from Zone 2 according to the term

$$S(1-\alpha)[r_2 X_{2,t}(1 - X_{2,t}/K_2)],$$

where $1 > S > 0$ is the survival rate of larvae diffused to Zone 1 from Zone 2, $(1 - \alpha)$ is the diffusion rate (a fraction $1 > \alpha > 0$ of larvae remain in Zone 2), r_2 is the intrinsic growth rate in Zone 2, and K_2 is the urchin carrying capacity of Zone 2.

The second equation in the dynamical system describes the dynamics of the urchin population in Zone 2. Note that the fraction of larvae remaining in Zone 2 reduces the effective intrinsic growth rate to αr_2 and we assume harvest in Zone 2 according to a second Schaefer production where $Y_{2,t} = q_2 X_{2,t} E_{2,t}$.

The third equation in the system assumes that effort in Zone 1 changes according to the first-order difference equation $E_{1,t+1} - E_{1,t} = \eta_1(pq_1X_{1,t}E_{1,t} - c_1E_{1,t})$, where $\eta_1 > 0$ is an effort adjustment parameter and $(pq_1X_{1,t}E_{1,t} - c_1E_{1,t})$ is profit (or net revenue or "rent") in Zone 1 in period t. The per ton, wholesale price received by divers is $p > 0$ and the unit cost of effort in Zone 1 is c_1. Where c_i is a unit of the effort index. If profit is positive, $(pq_1X_{1,t}E_{1,t} - c_1E_{1,t}) > 0$, dive hours increase and $E_{1,t+1} - E_{1,t} > 0$. If profit is negative, $(pq_1X_{1,t}E_{1,t} - c_1E_{1,t}) < 0$, dive hours decrease, and $E_{1,t+1} - E_{1,t} < 0$.

The fourth equation in the system describes the dynamics of effort in Zone 2 and is based on the same economic logic that positive profits will cause and increase in effort and that negative profits will cause a decrease in effort. We allow for the adjustment parameter, η_2, the catchability coefficient, q_2, and the cost per dive hour, c_2 to differ form the parameter values in Zone 1.

A bionomic equilibrium is a steady state where $X_{1,t+1} = X_{1,t} = X_{1,\infty}$, $X_{2,t+1} = X_{2,t} = X_{2,\infty}$, $E_{1,t+1} = E_{1,t} = E_{1,\infty}$, and $E_{2,t+1} = E_{2,t} = E_{2,\infty}$. Our 2ZPOA model has two steady states: (1) extinction, where $[X_{1,\infty}, X_{2,\infty}, E_{1,\infty}, E_{2,\infty}] = [0, 0, 0, 0]$, and (2) non-extinction, where biomass and effort levels are positive in both zones. The non-extinction steady state has the following analytic expressions:

$$X_{1,\infty} = c_1/(pq_1)$$

$$X_{2,\infty} = c_2/(pq_2)$$

$$E_{1,\infty} = (r_1/q_1)(1 - X_{1,\infty}/K_1) + [S(1-\alpha)/q_1](r_2(X_{2,\infty}/X_{1,\infty})(1 - X_{2,\infty}/K_2))$$

$$E_{2,\infty} = (\alpha r_2/q_2)(1 - X_{2,\infty}/K_2)$$

The local stability of either steady state can be determined by evaluating the Jacobian matrix of the dynamical system at the steady state of interest and calculating its eigenvalues. The Jacobian matrix for the 2ZPOA takes the following form

$$J = \begin{bmatrix} 1 + r_1 - q_1 E_{1,\infty} - 2r_1 X_{1,\infty}/K_1 & S(1-\alpha)(r_2(1 - 2X_{2,\infty}/K_2)) & -q_1 X_{1,\infty} & 0 \\ 0 & 1 + \alpha r_2 - q_2 E_{2,\infty} - 2\alpha r_2 X_{2,\infty}/K_2 & 0 & -q_2 X_{2,\infty} \\ \eta_1 p q_1 E_{1,\infty} & 0 & 1 & 0 \\ 0 & \eta_2 p q_2 E_{2,\infty} & 0 & 1 \end{bmatrix}$$

There are 17 parameters and initial conditions in the 2ZPOA model. The symbol, description, value and source are given in Table 3.1. The values for α, S, η_1, η_2, c_1, and c_2 were assigned and are therefore subjective, based on our understanding of larval dispersion from Zone 2 to Zone 1, survival of dispersed larvae, the response of effort to positive profits, and the cost of a dive hour in Zone 1 and Zone 2. In Table 3.3 we report the values for $[X_{1,\infty}, X_{2,\infty}, E_{1,\infty}, E_{2,\infty}]$ and the eigenvalues when the Jacobian matrix is evaluated at both the extinction and non-extinction equilibria.

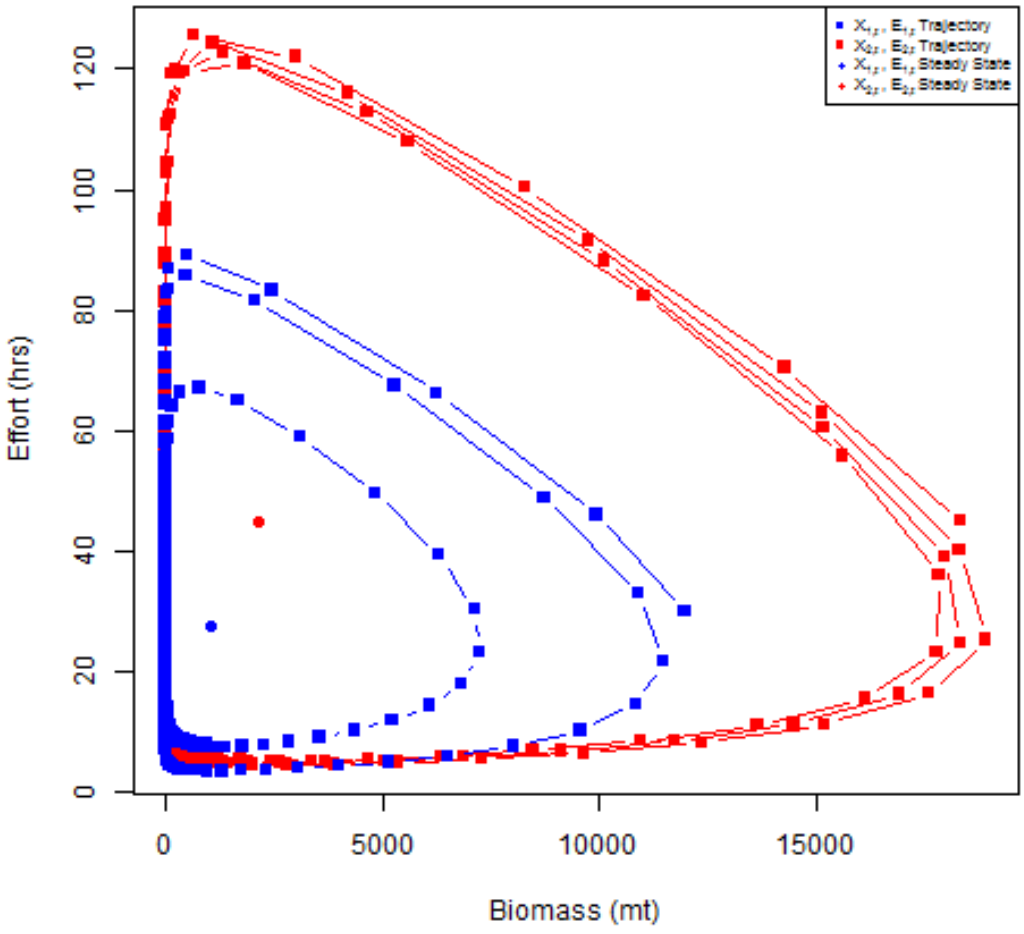
Table 3.3: Bionomic Equilbria and Eigenvalues

Equilibrium Type	Biomass and Effort Values	Eigenvalues
Extinction	$X_{1,\infty} = 0$, $X_{2,\infty} = 0$, $E_{1,\infty} = 0$, $E_{2,\infty} = 0$.	1.40 ,1.48 ,1.00 ,1.00.
Non-Extinction	$X_{1,\infty} = 1020.4$ (metric tons), $X_{2,\infty} = 2142.8$ (metric tons), $E_{1,\infty} = 27.6$ (hrs), $E_{2,\infty} = 45.1$ (hrs).	$0.9935 \pm 0.1390\imath$, $0.9853 \pm 0.1832\imath$.

The extinction equilibrium is not locally stable, with four real eigenvalues greater or equal to one. The non-extinction equilibrium is locally stable with two complex conjugates

with real parts less than one in absolute value. This analysis implies that when starting from positive, profitable biomass levels in Zone 1 and Zone 2, the points $[X_{1,t}, E_{1,t}]$ and $[X_{2,t}, E_{2,t}]$ will spiral in a counter-clockwise fashion and either converge asymptotically to $[X_{1,\infty}, E_{1,\infty}]$ and $[X_{2,\infty}, E_{2,\infty}]$ or converge to stable limit cycles with $[X_{1,\infty}, E_{1,\infty}]$ and $[X_{2,\infty}, E_{2,\infty}]$ as foci. For the parameter values in Table 3.1, we observe slow spiral convergence to $[X_{1,\infty}, E_{1,\infty}]$ and $[X_{2,\infty}, E_{2,\infty}]$ as shown in Figure 3.4.

Figure 3.4: Slow Spiral Convergence to $[X_{1,\infty}, E_{1,\infty}]$ (Red) and $[X_{2,\infty}, E_{2,\infty}]$ (Blue).



Changing η_1 or η_2 does not change the non-extinction values for $[X_{1,\infty}, E_{1,\infty}]$ and $[X_{2,\infty}, E_{2,\infty}]$, but may change the classification of the non-extinction equilibrium. A range of *eta* values may be explored to check if a the non-extinction values in Table 3.3 become foci of stable limit cycles instead of foci of stable spirals.

3.5 2ZPOA Non Stationary Non Steady State Model

We now consider a model where we expect the effort in Zone 1 and Zone 2 to vary. We set $q_1 = 0.014$ and $q_2 = 0.010$, $p = \$3,500$, $c_1 = 50,000$/dive-dragger year, and $c_2 = 75,000$/dive-dragger year. Variability in $E_{i,t}$ can result from changing weather conditions and other factors that affect the efficiency of divers and draggers. We use the objective function such that,

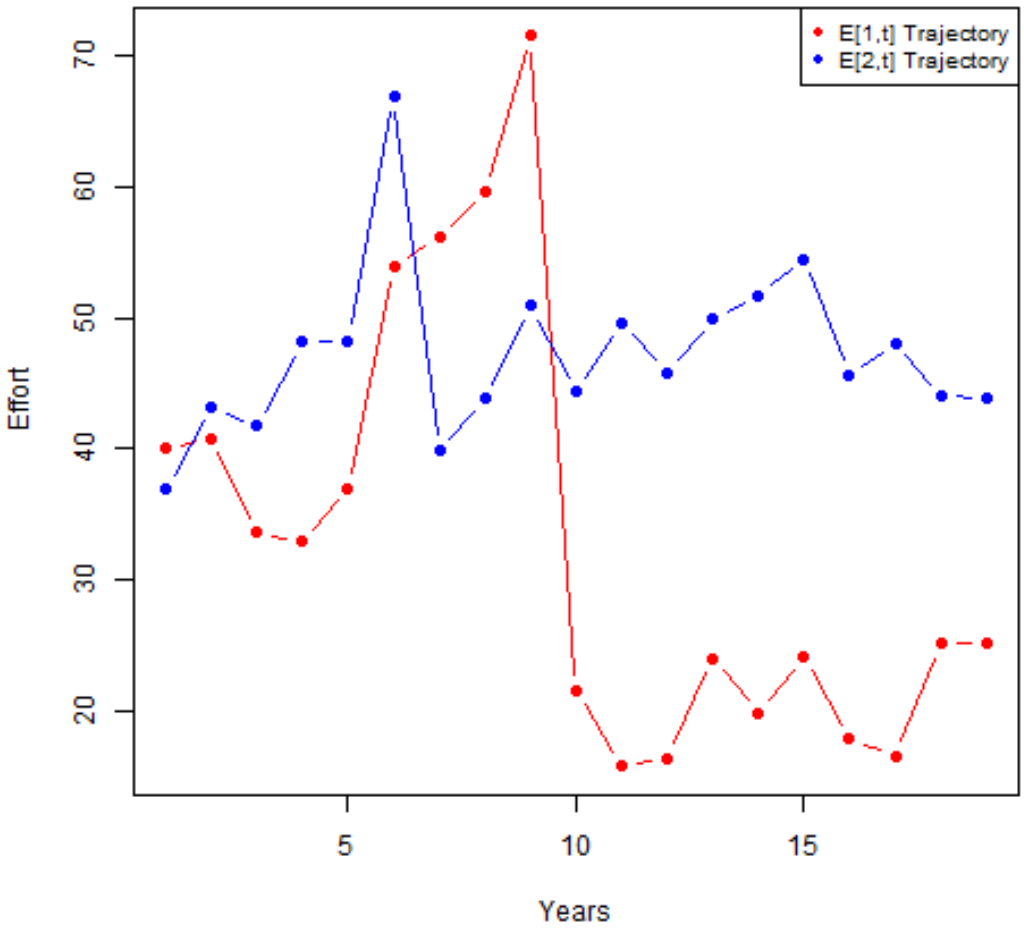
$$\underset{E_{1,t},E_{2,t}}{\text{Minimize}} \quad SSD = \sum_{t=1996}^{2013} \{(X_{1,t} - \hat{X_{1,t}})^2 + (X_{2,t} - \hat{X_{2,t}})^2\}$$

The objective function enables us to track Hunter's (2015) biomass estimates by choosing an $E_{i,t}$ that minimizes the sum of squares difference. With this model we can precisely mimic Hunter's (2015) stock estimates for Zone 1 and Zone 2. What's interesting is that $X_{1,\infty} = c_1/(p \times q_1) = 1,020$ and $X_{2,\infty} = c_2/(p \times q_2) = 2,143$, which are not far off from Hunter's values for $X_{1,2013}$ and $X_{2,2013}$.

If we observe that the value of E is gradually increasing we can argue that the divers or draggers were not as efficient as the draggers and divers who remain. With $E_{i,t}$ changing year to year the system never reaches a steady state. Now $E_{i,t} = E_i + \epsilon_{i,t}$, where $\epsilon_{i,t}\tilde{\mu}(a,b)$, and ϵ is uniform with $b > \epsilon_{i,t} > a$.

We observe $E_{1,t}$ ranging between 15 and 70 effort units while $E_{2,t}$ ranges between 36 and 70 (Figure 3.5). Given that the urchin fishery is distributed in a patchy environment, we suspect that $E_{i,t}$ must be higher in the early years of the fishery as divers and draggers exploited higher density patches (T. R. Johnson et al., 2013, 2012).

Figure 3.5: Changing Effort in Zone 1 and Zone 2



3.6 Optimizing Effort in the 2ZPOA Non Stationary Non Steady State Model

Can we do better than the current net revenue values in the fishery? We can address this question by doing a counter-factual analysis of effort in Zones 1 and 2 for the years 1995-2012. As shown earlier in steady state,

$$E_{1,\infty} = (r_1/q_1)(1 - X_{1,\infty}/K_1) + [S(1-\alpha)/q_1](r_2(X_{2,\infty}/X_{1,\infty})(1 - X_{2,\infty}/K_2))$$
$$E_{2,\infty} = (\alpha r_2/q_2)(1 - X_{2,\infty}/K_2)$$

The optimized expression for the optimal combination of E_1 and E_2 in the final function is denoted as:

$$\phi(X_{1,2013}, X_{2,2013} = \rho^{2012-1995}[p(q_1 X_{1,2013} E_1 + q_2 X_{2,2013} E_2 - c_1 E_1 - c_2 E_2)]/\delta$$

The initial spreadsheet starts with the effort levels that yield Hunter's estimates for$X_{i,t} i = 1, 2$, and $t = 1995, \ldots, 2013$. We calculate the present value of net revenues for $t = 2013, \ldots, \infty$ if the biomass levels, $X_{1,2013}$ and $X_{2,2013}$ are harvested so as to maintain those levels for the rest of time. We impose constraints on effort such that $40 \geq E_{i,t} \geq 0$ and biomass $X_{i,t} \geq 0$ for $t = 1995, \ldots, 2012$. Figure 3.4 on the next page summarizes the parameter values, initial conditions. The net present value of the fishery is $\pi = \$194,497,042$.

We can solve the problem by finding the optimal combination of $E_{i,t}$ when $X_{1,2013}$ and

Table 3.4: Counter-factual Analysis of Changing Effort in Zone 1 and Zone 2 - Initial Values

Time = t	$E_{1,t}$	$E_{2,t}$	$X_{1,t}$	$X_{2,t}$	$\rho^{t-1995}\ \pi_{1,t} + \pi_{2,t}$ [a]
1995	40.00	37.00	11978.00	18312.00	42,415,920.00
1996	40.82	43.19	8262.24	15736.04	34,346,189.50
1997	33.65	41.74	5989.87	13103.27	23,266,021.23
1998	32.98	48.16	5114.77	11573.21	21,213,913.51
1999	36.97	48.29	4471.74	9721.22	17,609,199.61
2000	53.99	66.84	3695.88	8399.40	19,667,527.90
2001	56.09	39.85	2210.03	5851.21	7,496,056.07
2002	59.67	43.85	1297.89	5859.42	5,671,958.36
2003	71.48	50.94	712.26	5632.61	4,389,148.56
2004	21.57	44.41	278.59	5032.71	3,102,521.72
2005	15.85	49.56	305.44	4866.67	3,420,404.63
2006	16.47	45.85	359.18	4466.54	2,569,856.98
2007	24.03	49.89	418.88	4289.48	2,397,046.83
2008	19.91	51.68	443.76	3956.54	2,101,109.57
2009	24.16	54.50	495.52	3596.65	1630,735.59
2010	17.96	45.68	523.43	3185.79	913,964.86
2011	16.66	48.09	598.10	3120.77	947,868.81
2012	25.21	43.98	693.69	2984.64	637,150.58
2013			720.62	2982.68	700,447.87
				π =	194,497,042.2

[a]Parameter values: $r_1 = 0.4$, $K_1 = 31,877$, $\alpha = 0.8$, $S = 0.001$, $c_1 = \$50,000$, $r_2 = 0.6$, $K_2 = 35,065$, $c_2 = \$75,000$, $p = \$3,500$, $\delta = 0.02$, $\rho = 0.9803922$, $q_1 = 0.014$, $q_2 = 0.01$, $X_{1,0} = 11,978$, $X_{2,0} = 18,312$

$X_{2,2013}$ are maintained. Figure 3.5 shows the optimal solution where the net present value of the fishery increases to $\pi = \$386,451,194$.

Based on the weighted dive dragger costs, we see that by greatly reducing effort in Zone 1 we can increase effort, E in Zone 2, even though ut has a higher cost compared to Zone 2. The optimization keeps the effort levels low up till year 2008 in Zone 2 and 2009 in Zone 1, after which effort is maximized up to the constraint of 40 effort, E units till 2012.

Table 3.5: Counter-factual Analysis of Changing Effort in Zone 1 and Zone 2- Optimized Values

Time = t	$E_{1,t}$	$E_{2,t}$	$X_{1,t}$	$X_{2,t}$	$\rho^{t-1995}\ \pi_{1,t} + \pi_{2,t}$ [a]
1995	0.00	26.35	11978.00	18312.00	14,914,249.73
1996	10.45	20.85	14969.92	17685.54	18,122,434.76
1997	15.55	25.97	15957.36	18205.07	24,971,260.35
1998	14.31	20.65	15672.12	17679.17	20,264,244.29
1999	14.61	25.86	15719.74	18235.77	23,174,394.57
2000	14.86	21.07	15693.54	17721.34	20,086,062.67
2001	13.96	25.53	15615.57	18194.56	21,603,831.06
2002	14.58	21.86	15750.21	17751.34	19,560,093.19
2003	14.47	24.00	15723.19	18077.46	20,320,052.40
2004	14.92	23.94	15726.24	17943.04	20,074,412.35
2005	13.93	22.29	15628.49	17853.85	18,231,401.99
2006	14.69	23.48	15769.23	18080.78	19,075,365.81
2007	15.78	25.53	15713.64	18038.84	20,158,608.68
2008	12.44	18.74	15430.51	17637.26	14,649,499.97
2009	12.03	40.00	15927.96	18539.08	24,057,414.22
2010	40.00	40.00	16433.82	15317.38	36,151,098.82
2011	40.00	40.00	10416.54	13331.06	24,825,358.30
2012	40.00	40.00	7389.35	11964.80	18,735,224.28
2013			5522.83	10962.33	74,761,86.62
				$\pi =$	386,451,194.07

[a]Parameter values: $r_1 = 0.4$, $K_1 = 31,877$, $\alpha = 0.8$, $S = 0.001$, $c_1 = \$50,000$, $r_2 = 0.6$, $K_2 = 35,065$, $c_2 = \$75,000$, $p = \$3,500$, $\delta = 0.02$, $\rho = 0.9803922$, $q_1 = 0.014$, $q_2 = 0.01$, $X_{1,0} = 11,978$, $X_{2,0} = 18,312$

3.7 Discussion and Future Research

This article presented three models calibrated to the Maine green sea urchin fishery, *circa* 1995. In 1994 the green sea urchin fishery had been partitioned into two zones and was generating approximately $20 million in revenues, ranking second behind lobsters in the State of Maine. Management by the state was not able to prevent over harvest, and by 2005 urchin biomass, particularly in Zone 1, had declined to levels where net revenue approached zero, symptomatic of a pure open access equilibrium.

Our two-zone, pure open access (2ZPOA) model, had dispersion of larvae from Zone 2 to Zone 1, resulting in a coupled, four-dimensional dynamical system. There were two steady states, extinction and a non-extinction. For our base-case parameter set, when starting from positive biomass levels, the extinction steady state was not locally stable while the non-extinction steady state was locally stable, exhibiting spiral convergence to $[X_{1,\infty}, E_{1,\infty}]$ and $[X_{2,\infty}, E_{2,\infty}]$. In the non-extinction steady state, biomass in Zone 1 had declined to less that 20% of carrying capacity while in Zone 2 it had declined to less than 30% of carrying capacity.

Our second model (2ZPOA) model, also had dispersion of larvae from Zone 2 to Zone 1, with an objective function that tracked Hunter's (2015) biomass estimates by varying effort levels in response to declining biomass. Varying E_i results in a non stationary, non-steady state model.

Our third model was a dynamic, mixed-integer model seeking to maximize the present value of net revenue by determining optimal proportional harvest policies, E_i, with constraints such that $40 \geq E_{i,t} \geq 0$ and biomass $X_{i,t} \geq 0$ for $t = 1995, \ldots, 2012$. Proportional harvest in Zone 1 begins in $t = 2$, while effort was optimally restricted to below 15 effort units from 1996-2009, and in Zone 2 from 1995-2008. The optimal combination of $E_{i,t}$ when $X_{1,2013}$ and $X_{2,2013}$ gives a solution that would result in a fishery with a net present value of approximately $386 million.

Ecologists studying the coastal Maine ecosystem and the green sea urchin fishery believe that the over harvest of urchins during the 1990s and early 2000s may have caused the ecosystem to "flip"to a low-urchin, high-kelp-crab, locally stable equilibrium. The decline in the urchin population resulted in a rise in the macro algae, which some ecologists believe caused the ecosystem to undergo a bifurcation, "ecosystem flip ". Despite increased regula-

tory interventions the urchin populations have not rebounded and repeated scientific studies have shown that high urchin biomass may be difficult to achieve. There has been a rise in the abundance of crabs and lobsters, which are being harvested (Kanaiwa et al., 2005; Ocean Tipping Points, 2017; Steneck et al., 2013; Vavrinec, 2003). In Zone 1 the urchins would appear to be economically extinct. The fishery has declined significantly. There are approximately 300 licensed urchin fishers in the entire state of Maine, only 60% of which are active at any given time. The bifurcation in the fishery may be modeled using a dynamical system. For such a system to generate a locally stable equilibria would require, at a minimum, three species: urchin, kelp, and crab. Consider the following system, written in general form as

$$
\begin{aligned}
X_{t+1} &= F_1(X_t, S_t, C_t; \omega, B_t) \\
K_{t+1} &= F_2(X_t, S_t) \\
C_{t+1} &= F_3(X_t, S_t, C_t)
\end{aligned}
$$

In the above system, X_t is the biomass of urchins in year t, S_t is the biomass of kelp (seaweed), and C_t is the biomass of crab. If urchin are being harvested in year t, $B_t = 1$ and harvest is $Y_t = \omega X_t$. Urchin feed on kelp and are pray (food) for crab. Crab need kelp for cover to reduce predation by other species. Starting from a low-urchin, high-kelp-crab equilibrium, this system would presumably have the following partial derivatives: $\partial F_1(\bullet)/\partial X_t > 0$, $\partial F_1(\bullet)/\partial S_t > 0$, $\partial F_1(\bullet)/\partial C_t < 0$, $\partial F_2(\bullet)/\partial X_t < 0$, $\partial F_2(\bullet)/\partial S_t > 0$, $\partial F_3(\bullet)/\partial X_t > 0$, $\partial F_3(\bullet)/\partial S_t > 0$, and $\partial F_3(\bullet)/\partial C_t > 0$. Denote the low-urchin, high-kelp-crab steady state as $[X_L, S_H, C_H]$ and the high-urchin, low-kelp-crab steady state as $[X_H, S_L, C_L]$. In nonlinear systems, locally stable steady states are often separated by a locally unstable steady state. Suppose extinction, $[0, 0, 0]$, is locally unstable and denote by $[X_U, S_U, C_U]$ the locally unstable steady state separating $[X_H, S_L, C_L]$ from $[X_L, S_H, C_H]$, where $X_H > X_U > X_L$. To return the coastal ecosystem to the economically more desirable $[X_H, S_L, C_L]$ one would need

to somehow move the system from the basin of attraction for $[X_L, S_H, C_H]$ into the basin of attraction for $[X_H, S_L, C_L]$. This might be accomplished by establishing a moratorium on the harvest of urchins (as in our mixed-integer optimization problem) and paying a bounty on the harvest of crabs.

There may be several possible forms for $F_1(\bullet)$, $F_2(\bullet)$, and $F_3(\bullet)$ which might exhibit the four requisite steady states and allow one to determine the levels of crab harvest which might move the system into the basin of attraction for $[X_H, S_L, C_L]$. This would be an interesting area for future research.

CHAPTER 4

MARINE RESOURCE DEGRADATION AND MALNUTRITION. A SPATIAL COMMUNITY MODEL OF WELL-BEING IN SMALL-SCALE FISHER COMMUNITIES IN INDONESIA

UNDERSTANDING THE EFFECT OF CLIMATE CHANGE ON FISHERIES AND FISHING COMMUNITIES: A THEORETICAL AND AN EMPIRICAL APPROACH

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Artisanal fisher communities are vulnerable to climate and weather-related risks and human-induced disturbances. Well-being in fisher villages is an outcome of the natural, human, and capital assets at the disposal of these fisher communities. Failure in the ability of the village to get access to at least one of these assets may affect socioeconomic outcomes. Malnutrition is a particularly strong indicator of low well-being. Therefore, I use the incidence of malnutrition in fisher villages to measure community well-being. I look at the relationship between well-being and coastal environmental degradation (natural assets), village level social factors (human assets), and economic characteristics (capital assets) by using a spatial autocorrelated Cobb Douglas production function of malnutrition at the village level. The model is used to explore the relevant determinants of well-being in fisher communities, and their relationship with neighboring assets. This paper then identifies variables of interest that are important control variables that will enable future researchers to establish a causal relationship between malnutrition in fisher communities and environmental degradation (induced by both local and global threats). Data on fishing gear, number and type of boats, presence of middle-men, access to markets, information, credit systems, fish species, landings, and rele-

vant ecological covariates is therefore required to accurately measure the level of resilience in fishing communities to ecological degradation. Using a socioeconomic nation-wide dataset on Indonesian villages as a case, I find a significant response between thermal and local threats in coastal coral reef ecosystems and the cases of reported malnutrition at the village level. Among the many significant findings of this study, the model predicts that the interaction effects of local and global threats to coral reefs further exacerbates malnutrition outcomes in fisher villages.

4.1 Introduction

Communities dependent on natural resources are vulnerable to climate and weather-related risks, and human-induced disturbances. Natural and human-induced disturbances that degrade the quality of the ecosystem also indirectly affect resource dependent communities' health and well-being (Fiorella et al., 2014). Research attempting to empirically establish the link between environmental factors and human well-being is growing rapidly. For example, research has linked the degradation of air, deforestation, and desertification to outbreaks of disease, poor long-term health and poverty traps (Graff Zivin & Neidell, 2012; Greenstone & Hanna, n.d.; Maccini & Yang, 2009; Toth, 2015). However, despite the increase in literature on environmental degradation and its impact of resource dependent communities, there is limited work on understanding the relationships between degradation in the marine environment and its linkages to well-being in fisher communities. Artisanal fisher communities are particularly vulnerable to changes in ecosystem dynamics, given that they derive their primary source of protein and nutrients from the fish they harvest. The Food and Agriculture Organization (FAO) defines artisanal fishing (or traditional/subsistence fishing) as, "the various small-scale, low-technology, low-capital, fishing practices undertaken by individual

fishing households (as opposed to commercial companies). Many of these households are of coastal or island ethnic groups."(Cochrane & Garcia, 2009). It is very important to understand the linkages between well-being, human-induced and climate-related degradation in marine ecosystems, especially with regards to artisanal fishing communities deriving nutritional value from the resource. A better understanding of these dynamics will help provide the necessary support to minimize the impacts for future communities.

Artisanal fishing communities are dependent on deriving a living from marine resources, such as coral reefs, that support the world's most biodiverse variety of sea life. Coral reefs are of particular importance since they provide a safe haven for juvenile fish, lobsters, crabs, and shellfish. Invariably, the well-being of traditional artisanal fishers depends on the health of coral reefs. In addition, coral reefs have substantial economic and cultural significance for fishing and recreation. The causal linkage between the health of the reef and its effect on well-being is based on complex biophysical mechanisms. The productivity of natural capital such as fish and coral reefs determine the well-being of communities (Barrett, Garg, & McBride, 2016). There is an alarming concern over the productivity of coral reefs: they are exposed to pressures from global warming and local pollution, as well as and over fishing and illegal fishing by commercial and subsistence fishers. Weak governance and ineffective marine conservation planning compound the problem of depleted marine resources.

The well-being of traditional artisanal fishing communities also depends on socioeconomic factors. These include access to education, health facilities, credit, technology, and alternative income opportunities. Other socioeconomic factors include poverty alleviation programs, quality of governance of the fishery resource, strength of the community-based management initiatives, access to global and local markets (fish auction locations), role of the middle-men and other macro factors. Poverty alleviation strategies often focus on ameliorating social and economic challenges, often overlooking the marine conservation pertinent

to addressing the global and local threats to marine resources.

In the field of public health and development economics, various indicators have been identified to describe the nexus of food security and nutritional health (Heltberg, 2009). Malnutrition is an indicator of a nutrition health outcome. Malnutrition as a non-monetary indicator of well-being and deprivation, is widely considered as a better alternative to income and expenditure based monetary indicators that are used to compare poverty levels across regions (Deaton, 2001; Ravallion, 2001). The primary objective of this paper is to provide empirical evidence linking malnutrition in fisher communities to degraded coral reef ecosystems. An outcome of this objective is that this exercise helps identify the relevant determinants of well-being as exemplified by the level of malnutrition in fisher communities.

Degradation of the reef can affect malnutrition through three main channels. First, nutrition in fisher communities is highly dependent on wild sea food as the main source of protein and micro-nutrients (Golden et al., 2016). Fish are a critical source of proteins, minerals, macro and micro nutrients such as vitamin B_{12}, and fatty acids (DHA omega-3) . A community can be identified as nutritionally vulnerable if their nutrient supply is less than double the estimated average requirement (EAR), and if they derive more than 10% of their vitamin A or zinc, or more than 5% of their iron from fish (Thilsted, James, Toppe, Iddya, & Subasinghe, 2014). Artisanal fishing communities are critically dependent on wild-caught fish for sustenance, especially fisher communities that rely solely on subsistence fisheries. Unsustainable fishing practices are known to be especially detrimental for communities that are dependent on marine resources [1]. Resource degradation has a direct impact on resource-

[1]Resource-dependent communities are predominantly single industry communities where the interface between natural environment and society is pronounced due to the dependence on a single economic base. For example, in a fishing community, the economy is predominantly dependent on marine resources. Therefore, the economic specialization is closely tied to the specific resource extraction activity. Randall and Ironside (1996) give a good overview of the literature on resource-dependent communities. Fisheries based resource-dependent communities experience unpredictable variations in fish price, factor prices, due to stochastic variability in the abundance of fish populations. This high inter-annual variability in price, factor prices

dependent communities' income and nutritional status (Allison & Ellis, 2001). Malnutrition and the diseases associated with it are persistently higher in fishing villages (Salagrama, 2006). The problem of food security is intensified during the non-fishing season and especially following a natural disaster. Even within households, there exist intra-household differences in access, quality, quantity, and frequency of food consumption. Difficulty in obtaining sufficient nourishment results in vitamin deficiency, leading to higher cases of diarrhea, respiratory infections, malnutrition and other communicable diseases. The quality of public health services in remote coastal villages is also a contributing factor. These factors result in high infant mortality rates (Salagrama (2006)).

Alternatively, persistent malnutrition in children can be seen as a health shock that may affect long term outcomes, such as educational attainment or ill health that determines long run well-being (Maccini & Yang, 2009). This perpetuates a cycle of lower well-being, ill health and disadvantages in the ability to generate income.

The second channel that links degraded reefs to malnutrition is climate-driven coral bleaching. Bleaching is emerging as one of the greatest threats to the coral reef ecosystem (Graham et al., 2007). Coral reefs are being degraded at an accelerated pace due to local-scale and global-scale stressors mentioned earlier. Mass coral bleaching is primarily caused by anomalies in water temperature through heat stress- resulting in thermally induced coral bleaching. Based on global sea surface temperature (SST) forecasts there is a likelihood of repeat occurrences of coral bleaching every five years (Sheppard, 2003). A recent study with

and catch result in high income variation (Andersen, 1982; Kasperski & Holland, 2013). The high degree of risk that is associated with this variation has a direct impact on fishermen well-being. Declining incomes from fishing and increased uncertainty from stock depletion, uncertainty from changes in fishing regulations affect job satisfaction, well-being (Pollnac, Seara, & Colburn, 2014) and psychological health of fishermen (Pollnac & Poggie, 2008). It is well-documented that fishing is a risky occupation (D. G. Johnson, Thomas, & Riordan, 1994). High inter-annual variability in catches and prices many fisheries leads to variability in the income and high levels of financial risk derived by fishery participants. In general, other resource dependent communities also face similar financial risk.

the ARC Center of Excellence for Coral Reef Studies at James Cook University in Queensland has also determined that the previous coral bleaching events have subjected corals to sub-bleaching stress prior to reaching temperatures that cause bleaching. Such a temperature regime confers thermal tolerance that increases coral resilience to temperature-induced mortality. Based on future climate projections, the supposedly protective temperature regime will be lost, subsequently increasing the rate of degradation. Coastal regions with high levels of local pollution through agricultural run-off, municipal waste effluent, deforestation and overfishing are more susceptible to coral bleaching and permanent die-off when anomalously warm waters stress the corals. Stress in corals can trigger a mass exodus of photosynthetic algae, called *zooxanthellae*, from their cells, upending their metabolism (Ainsworth et al., 2016).

Third, coral and rocky reefs serve as nurseries for fish stocks. The short-term effects of coral bleaching is manifest in species that specialize on live coral for diet, shelter, or recruitment habitat. In the medium to long term, overall species richness can reduce if the physical matrix of the reef collapses. The medium to long-term impacts on fisheries size structure are not fully understood. It is likely that if there is a loss in structural complexity, there will be an 8-10 year lag effect before the impact of coral bleaching is noticeable. This is because individuals take time to recruit to the fishery (Graham et al., 2007). Consequently, coastal fisher communities are expected to be greatly impacted by these events (UNEP, 2006), albeit there will be a lagged effect given the skewed impact of coral reef damage on juvenile life stages of fisheries (Graham et al., 2007).

The second and third mechanisms are purely ecological ones. In this paper, I will provide evidence to support the claim that there is a social-ecological response in the effect of coral bleaching and local threats on the incidence of malnutrition in fisher resource-dependent communities.

Indonesia is a particularly good case to address this relationship, given the large population (6.4 million) of artisanal fishers, and the fact that Indonesia has 78% of the world's coral reefs that have been threatened by massive coral bleaching events in 1998, 2010, and 2016. It is estimated that in 1998 the anomalously high sea surface temperatures killed more than 90% of shallow corals in the Indian Ocean (Sheppard, 2003). Some parts of Indonesia experienced these anomalous sea temperatures that passed coral bleaching thresholds (Goreau, Mcclanahan, Hayes, & Strong, 2000). Another reason why Indonesia is a good case to study this relationship is because Indonesia ranks fifth in world on a key indicator of malnutrition, that is stunted growth of children under the ages of five. Despite the economic progress and the improvements in health facilities and of water and sanitation services during the 1980's and 1990's, the Indonesian health system has a limited capacity in implementing nutrition interventions aimed at improving maternal and child under-nutrition. There has been no progress in reducing the rates of stunting between 2007 (36.8%) and 2013 (37.2%). In Indonesia approximately 87 million people are vulnerable to food insecurity and 9.5 million children under the age of five are malnourished. While 3 million children under the age of five suffer from wasting, 57% of the children under the age of two in rural areas have been diagnosed as anemic (Shrimpton & Rokx, n.d.; Winata, 2014). According to the World Food Programme[2], malnutrition costs Indonesia $\geq$5 billion annually in terms of long-term loss of productivity from poor education and diminished physical capability (Winata, 2014). While these statistics are for the entire country, official statistics do not break them down by occupation. An indicator for nutrient deficiency in fisher families can be obtained from the Indonesian Family Life Surveys (IFLS). The trends in iron deficiency (fish is a rich source of iron), anemia have been improving in Indonesia, however, trends in anemia measured as

[2]The following hemoglobin cut-offs were used to define anemia, in accordance with the WHO: 11.0 g/dL for children $\leq$ 5 years; 11.5 g/dL for children 5$-$ $\leq$ 12 years; 12.0 g/dL for children 12$-$ $\leq$ 15 years; 12.0 g/dL for non-pregnant women $\leq$15 years; 11.0 g/dL for pregnant women $\geq$15 years, and 13.0 g/dL for men $\geq$15 years $\leq$12

(% $\geq$ 12g Hb/dl) children under the age of 5 in fisher households is 74%, and is 44% for children ages 5-10, compared to a national average of 69% and 37% respectively. Under the Welch-Two Sample t-test the difference in means is statistically significant (Strauss et al., 2004; Strauss, Witoelar, & Sikoki, 2016; Strauss, Witoelar, Sikoki, & Wattie, 2009). This paper takes a multi-disciplinary approach that contributes to the development economics and marine policy literature by emphasizing the main determinants of well-being in poor fisher communities. The results have policy implications for identifying effective strategies to be implemented in marine conservation and fisheries management in order to reduce thermal and local anthropogenic threats to fish stocks to promote nutritional security in fisher communities. Resulting insights also provide a rationale for developing fisheries specific modules in household surveys that facilitate a better understanding of the social-ecological poverty dynamics in fisher communities.

Based on the literature review, much like the rest of the fishing industry, there are no specific studies on the ecological impact of degradation on fisher communities in Indonesia (Chaijaroen, 2015; Collier, Hadikoesworo, & Malingreau, 1977; McClenachan, O'Connor, & Reynolds, 2015; Yuerlita, Perret, & Shivakoti, 2013). There are no existing studies that robustly control for factors that impact well-being in fisher communities, such as degraded water quality from local and global threats. Individual research based on fisher communities in Indonesia has focused on specific provinces, small fisher communities or islands with little empirical evidence for generalizability to the larger Indonesian context (Kramer, Simanjuntak, & Liese, 2002; Sievanen, Crawford, Pollnac, & Lowe, 2005; Stanford, Wiryawan, Bengen, Febriamansyah, & Haluan, 2013, 2014; Verité, 2012; Yuerlita et al., 2013; **?**). These studies do provide valuable insight into the social-ecological[3] dynamics of small-scale fishers in

[3]Social-ecological systems are comprised of inseparable and indivisibly linked human and natural components. This concept was proposed by Berkes and Folke (1998), to emphasize that changes in ecosystems impact human societies, and the response of human societies to these changes can exacerbate or ameliorate the ecosystem. This concept has been applied to marine ecosystems by several studies and reviews, to name

selected villages, islands or for a representative sample at the provincial level. While the social-ecological dimensions of resource use are often emphasized in marine policy, limited attempts have been made to understand the livelihoods of fishers (Ferse, Knittweis, Krause, Maddusila, & Glaser, 2012) with respect to local and global threats that affect the ecological linkages between fishers and their resource-use. Neither of these studies have included long-term oceanographic anomalies to account for spatial ecological variation across small-scale fishermen communities. These studies have overlooked the utility arising from quantitative longitudinal surveys that focus specifically on fisher communities using satellite-based environmental data while differentiating spatial differences in environmental and social vulnerability. This paper addresses some of these thematic and methodological gaps and attempts to answer one major question: is there a strong relationship between degradation of coastal ecosystems and malnutrition in fisher communities in Indonesia?

This paper is organized as follows: Section 2 provides the context for coral reef degradation in Indonesia and the incidence of malnutrition in fisher villages, and Section 3 describes the community model. Section 4 describes the data and section 5 discusses the estimation results. Section 6 discusses the implications of the results and Section 7 concludes with policy implication for marine resource management.

4.2 Background- The Coral Triangle, Indonesia

The Coral Triangle extends from Indonesia to Papua New Guinea and the Solomon Islands, and northward to the Philippines. This region is the global hotspot for marine biodiversity. Indonesia has 5.8 million km^2 of marine resources in its exclusive economic zone. The 5.8

a few (Blythe, 2015; Campbell, Kartawijaya, Yulianto, Prasetia, & Clifton, 2013; Dolan & Walker, 2006; Perry et al., 2011)

km^2 archipelago waters contain 81,000 km of coastline and 17,000 islands (Alder, Sloan, & Uktolseya, 1994). Indonesia contains 78% of the world's coral reefs (Dutton, Djohani, Sastrapradja, & Dutton, 2009). The Indonesian fishery sector is of particular importance owing to the presence of coral reef biodiversity, within the Coral Triangle. Indonesia has the highest diversity of reef fishes within the Coral Triangle, including many endemic species (Allen, 2008). These shallow water ecosystems support intense commercial and subsistence utilization (Alder et al., 1994). Indonesia's fishery sector provides about 8.9 million tons of inland and marine catch annually, generating income for approximately 6.4 million fishermen, 95% of which are artisanal fishermen. The fishery sector contributed to 3% of national GDP in 2012 (FAO 2011), which represents an increase in recent years compared to the contribution of US5.47 billion in 2004, which was 2.4% of the GDP (Hoegh-Guldberg et al., 2009). The total employment generated from the marine fisheries sector in 1999 (4.8 million jobs) and 2005 (7.3 million jobs) has increased. The fisheries sector therefore provides jobs, sources of protein, and supports international export trade (Hoegh-Guldberg et al., 2009).

The fishing industry in Indonesia faces many local and global challenges. At the local level some of these challenges include weak monitoring and surveillance, overfishing, illegal unreported and unregulated (IUU) fishing FAO (2011). The approximated annual cost of illegal fishing has been estimated at $3 billion (The Economist, 2015). Consequently, almost two-thirds of the coral reef in Indonesia is locally threatened by over-fishing, and about half of the coral reefs are threatened from destructive fishing practices (World Bank, 2014). There are also challenges that fisher communities face from a local policy perspective that further marginalize fisher communities. Indonesia's National Decentralization Law (1999) along with the Fisheries Law (2004) and the Coastal Zone Management Law (2007, revised 2014) form the basis of the fisheries and marine conservation policy. The laws have provisions for tackling most of the challenges faced by the fisheries sector. However, these laws overlook the man-

date of local government and coastal communities for resource utilization and management (Ferrol-Schulte, Gorris, Baitoningsih, Adhuri, & Ferse, 2015). For example, institutional failure can be seen in the National Decentralization Law (2001) which empowered district level administrators to utilize local resources (forests and marine) for income generation. This law has created negative outcomes for poor fisher communities, because the law dis-empowers artisanal fishers effective control over their own resource, while giving incentives to commercial fishermen to harvest the resource. This leads to conflict between resource utilization between local communities and commercial enterprise. Despite the presence of traditional community based management self-regulation amongst local communities, inshore reef fisheries and island forests cannot be safe-guarded against commercial over-exploitation (Dutton et al., 2009). Invariably excluding the legal mandate of local communities over the resource leads to diminished capacity within the communities for sustainably continuing their livelihoods and decreases their threshold for tolerance from external shocks, hence increasing poverty and a decline in wellbeing.

At the global level, there is evidence to suggest that climate induced changes, such as sea-level rise, ocean acidification, and rising sea temperatures, alter species environmental tolerance, ocean productivity, ecosystem function (Ruckelshaus et al., 2013). Invariably, these global and local challenges impact (albeit through a complex causal chain) fisher livelihoods and well-being at the household and community level (Badjeck, Allison, Halls, & Dulvy, 2010; Brander, 2010).

Despite the significant contribution to overall national income, the many obstacles and challenges faced by fisher communities make it difficult for artisanal fishers to make a decent living from fishing. The individual fisher and fish farmers have a low standard of living, low income and an absence of fair credit and insurance programs. Ultimately, the consequence of these obstacles is visible in the nutritional value derived from subsistence fishing. Fishers

who rely on their fish catch as the major source of food are vulnerable in many respects. If fishers derive more than 10% of their vitamin A or zinc, or more than 5% of their iron from fish they are identified as nutritionally vulnerable. Fish accounts for 54% of animal protein intake in Indonesia (Thilsted et al., 2014). Based on this metric for nutritional vulnerability, fisher communities in Indonesia are most reliant on fish and most vulnerable to micronutrient malnutrition (Golden et al., 2016). While we are unable to address each of these challenges, especially global trends, we need to first make a compelling argument regarding a link between malnutrition and degraded ecosystems. Second, we need to understand the determinants of malnutrition in fisher communities, to enable policy makers to empower fisher communities and make them more resilient. The following section will describe the main determinants of fisher well-being, based on a review of the literature.

4.3 Determinants of Fisher Well-being

The main determinants of fisher well-being can be divided into three broad categories: natural assets, human assets, and capital assets. Each of these will be discussed with respect to fisher communities and will form the basis of the community model.

4.3.1 Natural Assets

Small-scale fishers depend on the coastal ecosystem to sustain their main source of livelihood. The coastal ecosystem's capacity to sustain fish stocks is dependent on the stressors of marine fish stocks, on fishing and marine or land based activities, and on global climate change threats. Coral reefs in Indonesia are threatened by the incidence of anomalous increases in

sea surface temperature. Based on SST forecasts there is a likelihood of repeat occurrences of coral bleaching every five years (Sheppard, 2003). Local threats include localized anthropogenic activities, including declining water quality, over-exploitation of resources, sewage discharge, destructive fishing, and overfishing, which is threating over 65% of the coral reef (Hoegh-Guldberg et al., 2009). Increased local threats are known to affect the quality of coral habitat and induce disease in the coral. These multiple stresses are compounding to reduce the resilience of these fragile ecosystems (Viets, 1998). The health of inshore coral reefs is also associated with the delivery of increased loads of sediments, nutrients, and toxins via flood river plumes (river plumes). Given that there are similar challenges associated with monitoring the responses of coral communities to changing water quality (based on in situ water quality data), remote sensing can be used to identify the differences in color of river plumes from ambient marine waters. It is not possible to directly measure natural assets: the state of natural assets can be identified using indicators such as presence of water and soil pollution, chlorophyll-a, forest loss, thermal threats such as warming sea temperatures. Warming sea surface temperature (SST) can induce coral bleaching, and ocean acidification (driven by increased CO_2), which can reduce coral growth rates. Local threats such as coastal development, watershed-based pollution, marine-based pollution and damage, overfishing, and destructive fishing are important factors in determining the state of the resource (L. Burke & Reytar, 2011). A productive resource is expected to have lower levels of local stressors such as pollution and sediment transport (O'Leary et al., 2017) and healthy sea grasses that can ameliorate seawater pollution from human-origination bacteria present in terrestrial effluent (Lamb, Water, Bourne, & Altier, 2017). Although there are no direct measurement of seawater pollution in Indonesia, the degree of water pollution can be assessed using the chlorophyll-a as a proxy for water clarity. The degradation in these natural assets would implicitly impact the nutritional status of fisher communities (Golden et al., 2016), however, there are no studies that explicitly determine a plausible pathway for this

relationship. This paper will attempt to derive this relationship. What we do know is that there is substantial empirical evidence that establishes causal linkages between environmental degradation and well-being in resource dependent communities (Maccini & Yang, 2009; Toth, 2015), among others.

4.3.2 Human Assets

The literature has already established that human assets such as level of education, health, and schooling are key indicators of well-being. For example, well-being in fisher households is determined by access to diversified livelihoods, such as farming or other alternate income opportunities that can complement income from fishing (Yuerlita et al., 2013). The presence of social capital, such as low crime rates, can also facilitate well-being (Stanford et al., 2014). Specifically in Indonesia, provinces with a higher concentration of health clinics have lower than average child mortality rates, and average rates of child malnutrition (Lanjouw & Pradhan, n.d.). Research in Indonesia has also empirically established that investments in primary schools has led to increase in average years of education which translates into increases in wages by $1.5 - 2.7\%$ for each school built (per 1000 children) (Duflo, 2000). In addition, income has been associated with a higher consumption of fish (Fiorella et al., 2014). Since malnutrition is a key component of well-being, we are going to explore and define how these factors affect malnutrition in fisher communities.

Studies that focus on the empirical evidence of linkages between education, health and well-being can help identify important determinants of malnutrition in fisher villages. Fishermen live in squalid crowed settlements, with little to no alternative job opportunities (Fox, Adhuri, Therik, & Carnegie, 2009). The presence of alternative job opportunities and proximity to large cities (where income generating opportunities might be higher) can be

avenues for increasing well-being. Well-being in fisher households is determined by access to diversified livelihoods, such as farming or other alternate income opportunities that can complement income from fishing(Yuerlita et al., 2013). The presence of social capital (Stanford et al., 2014), such as low crime rates, can also facilitate well-being. Human and social capital components such as leadership, trust, advocacy, administration, accountability, and transparent governance are also important for alleviating poverty, especially in marginalized fisher communities (Stanford et al., 2014). The utilization of public sector services is linked to the provision of health cards through a social security program that is distributed to poor households, which get access to free health care services. Public schools have higher rates of return to education compared to private schools, although the value added in private schools is higher than public schools, given students in private schools start out at a lower level. The returns to education (earnings after graduation) are higher for those who attend public schools compared to Islamic, non-religious private, and private Christian schools. The number of schools at the level of the village need to be disaggregated (Bedi & Garg, 2000; Lanjouw & Pradhan, n.d.). Investments in primary schools have also led to increase in average years of education which have translated into increase in wage by $1.5 - 2.7\%$ for each school built (per 1000 children) (Duflo, 2000). The Indonesian government spends 0.5% of the GDP on health (3.5% of total government expenditure). Provision of health is best measured using input indicators in health and education and there are marked disparities in regional spending on health and education across the archipelago. In predominantly public schools, there are low pupil teacher ratios recorded in Yogyakarta, Bali, Central and South Kalimantan, and North Sulawesi, high ratios recorded in West Java, West Nusa Tengara and East Timor. In general, private sector public schools have higher student teacher ratios. There is a higher concentration of hospitals in North Sumatra, Jakarta, Yogyakarta, Bali and North Sulawesi, and a higher concentration of health clinics is found in Bengkulu, East Timor, South and East Kalimantan, South East Sulawesi and Irian Jaya. Provinces with

the higher concentration of health clinics have lower than average child mortality rates, and average rates of child malnutrition (Lanjouw & Pradhan, n.d.). School enrollments and the number of visits to health centers are also good indicators, however these are not recorded in the PODES. Private schools that are utilized by poor households provide low cost, low quality education to the poorest quintile. The high cost of high quality private schools caters to the richest quintiles. Therefore, the number of public and private schools is an indicator of the quality of education in fisher villages (Lanjouw & Pradhan, n.d.)

4.3.3 Capital Assets

Capital assets, such as motorized boats, or access to boats, have a theoretical relationship to malnutrition. The quantity of fish harvested by an artisanal fisher directly translates to the proportion of fish that can be sold and the amount that can be consumed by household members. For example, there are marked differences in the resources owned by artisanal and commercial fishers. Artisanal fishers own wooden boats, canoes, and very rarely a powered motor boat. Artisanal fishers rely on reef fisheries closer to the shore and harvest fish with family members, selling a smaller proportion of their fish catch (less than 100 kg fish per day) to fish traders (Kramer et al., 2002). Motorization increases the number of locations and distances small-scale artisanal fishers can travel to harvest fish (C. Pet-Soede, Van Densen, Hiddink, Kuyl, & Machiels, 2001). The presence of motorized commercial vessels is an indicator of over-exploitation and depletion to in-shore traditional coastal grounds. The presence of motorization may be ideal for small-scale fishers, however too many fishers harvesting a limited resource may also relate to depletion of the resource (Collier et al., 1977).

Capital assets also consist of access to credit systems, various cooperatives, religious

support groups (mosques, churches), labor organizations, poverty alleviation programs. The relationship of such assets to malnutrition is not directly observable, or as evident. However, the development economics literature has established the impacts of increased credit and insurance systems (formal or informal) on well-being and the ability of households to generate income (Barnett & Barrett, 2008). For example, the presence of credit systems is vital for fishers, especially during the lean months. Middlemen usually provide credit, and also dictate the terms of fish prices. Fishers in remote villages are charged more exploitative prices for credit by middlemen (Salagrama, 2006). In addition, poor infrastructure, or lack of fish auction locations constrain fishers access to international or domestic markets. Therefore, any additional fish catch may go to waste, if fishers have no way of processing the fish, or selling it fresh. In addition, fishers face economic and environmental threats, communal conflicts, ethnic tensions, shifting governing systems, and idiosyncratic shocks (such as death of a head of household or loss of capital asset) at the household and community-level (Schwarz et al., 2011). The capacity of the community to help individual fishers cope with these shocks is important in preventing fishers from falling into poverty. Various cooperatives, religious support groups (mosques, churches), labor organizations, poverty alleviation programs can all provide the necessary capital to fishers during times of natural or individual idiosyncratic shocks.

Given that capital assets are relevant in determining well-being, we are going to explore and define how these factors relate to malnutrition in fisher communities. Access to these three assets clearly impacts well-being and therefore malnutrition. For the purpose of this paper, we will use these factors as key control variables that can help us isolate the relationship between environmental degradation and malnutrition in fisher villages. The following section will describe the theoretical model and identify potential estimates that will provide strong empirical evidence for the positive relationship between environmental degradation

and malnutrition in fisher villages.

4.4 Theoretical Model

The empirical work is motivated by well-being and poverty at the macro village scale (Indonesian *desa*) where institutional, geographic, and coordination or technology failures result in lower levels of well-being. The main motivation is understanding the determinants of well-being in fisher communities. We extend the Cobb-Douglas production function to estimate village scale malnutrition levels as a function of physical, human and natural capital. The production of malnutrition (as we would like to coin the term) is viewed as a function of the human, physical and natural capital in the village. To account for spatial dependencies, a conditional autoregressive (CAR) framework (Bivand, 2007) will be nested in the Cobb-Douglas production function.

The spatial autocorrelated residuals are denoted as,

$$\upsilon_i|\upsilon_{-i} \sim Normal(\frac{1}{N_i}\sum_{j=1}^{n} a_{ij}\upsilon_j, s_i^2) \tag{4.1}$$

where υ_i is the spatial autocorrelated residual, μ_i is the mean of the neighborhood set and $s_i^2 = \sigma_u^2/N_i$ is the variance. The parameter σ_u^2 controls the variation between the spatially structured random effects. The Cobb-Douglas production of well-being in the village is modeled by,

$$MN = K^{\beta_1} L^{\beta_2} N^{\beta_3} \tag{4.2}$$

where $\beta_1+\beta_2+\beta_3 = 1$. I modify the Cobb-Douglas model to include environmental drivers

such as thermal threats (T) as separate from natural capital (N). Given the spatially explicit nature of the data I also include fixed and random effects within the CAR framework. The spatially explicit production function, along with control variables takes the form,

$$ln(MN_{it}) = \beta_0 + \beta_1 K_{it} + \beta_2 L_{it} + \beta_3 N_{it} + \beta_4 T_i + \upsilon_{it} + \nu_{it} + \epsilon_{it} \tag{4.3}$$

where β_1 denotes the output elasticity of labor, and β_2 denotes the output elasticity of capital. N denotes a vector of all proxies for the natural capital, and β_4 denotes the coefficient on T that is the level of thermal and local threats to the coral in the vicinity of the village. The vector of controls for labor (L) include an indicator for the presence of unmotorized boats, motorized boats, and fish and agriculture auction places. The number of schools, number of incidences of disease, number of cooperatives, and all other village level assets that are facilitate labor productivity. The vector of controls capital inputs (K) includes material assets such as number of televisions, telephones, number of financial institutions, types of transportation, presence of markets, number of health facilities, and availability of electricity. The vector of controls for the ecological system includes (N), forest loss, a proxy for water quality, proxies for local threats, and (T) as a proxy for thermal threats. The parameter ν_i is the unstructured independent residual, $\nu_i \sim N(0, \sigma_\nu^2)$. The CAR structured as the Besag-York-Mollié (BYM) model comprises of υ_i along with the exchangeable random effect ν_i (Besag et al., 1991). Therefore, $\zeta_i = \upsilon_i + \nu_i$ are the spatial structured and unstructured components at the village (*desa*) level that account for spatial autocorrelation, and ϵ_{it} is the regression residual. The dependent variable MN is the number of cases of malnutrition in village (*desa*) i at time t.

Although we use all the available data at the village level to identify the production of malnutrition there are some limitations to our data that could potentially bias the coeffi-

cient of interest: (1) the omitted variable bias that occurs due to the absence of information related to fishing effort, fishing technology, illegal fishing practices, measures for community resource management practices, degree of dependency on resource, alternate income resources, access to education, health and sanitation services, and social capital; (2) Local threats such as illegal fishing practices that could be endogenous to all fisher communities. Fishing communities are geographically located in coastal regions within the vicinity of coral reefs that support a vibrant community of exploitable fisheries. Therefore, local threats to the reef only occur in regions that predominantly have fisher communities indicating a high dependence on reef based fisheries.

We make the assumption that thermal threat is exogenous to the presence of malnutrition in impoverished fisher households in Indonesia. This can be justified on the premise, that the 1998 coral bleaching event was due to sea surface temperature anomalies that were well-above temperature thresholds that corals could sustain. The anomalies were unprecedented and affected only certain coral reefs in the Indonesian archipelago. It is also assumed that reefs exposed to poor water conditions were less resilient to recovery. This assumption can be tested in different ways. First, the sample can be split between fisher and non-fisher villages, farm and wild capture fisheries, to test the exclusion restriction by investigating the alternative population (fisher villages not dependent on wild-capture fisheries or fisher villages that are not at the coastal) that ought not to be affected by coral bleaching. The falsification test will help determine whether the alternative population would be affected by the potential confounders.

Robustness checks can be conducted to ensure that the coefficient on β_4 Thermal Threat is tested for the evidence of structural stability, and this is done with the inclusion of a range of relevant control variables that are known in the literature to impact malnutrition in fisher communities, including the controls that are related to capital, labor and

natural assets. These controls include variables that represent social disruption (crime), infrastructure, wealth (boats) , occupations, specifically relevant to fisher communities. The robustness checks are further discussed in the Appendix in Table C.1 . The inclusion of predictor variables will be done carefully to ensure that we account for the bias variance trade off. All possible predictor variables will not be included as we run the risk of inflating the variance of the estimates. Therefore, in order to overcome the challenges associated with multicollinearity, variance inflation and model parsimony, we use backward and forward step-wise regression to identify the best set of predictors. These steps are used to identify a subset of the village level controls and environmental controls instead of using a dimension reduction strategy such as principal component analysis. Summary statistics for the relevant data are shown in Table 4.4. These variables are selected by identifying all possible controls relevant in the literature, and then using a subset for the final analysis. In the final analysis a subset of the covariates given in Table 4.4 are used in the linear and spatial Cobb-Douglas community model.

4.5 Data

The village-level data were obtained from the Village Potential Statistics (PODES) conducted by Central Bureau of Statistics, Indonesia. Village level socio-economic data for over 68,000 villages in Indonesia is collected periodically. The survey covers all the villages (*desa*s) in Indonesia. We use the PODES data for the years 2000, 2008 and 2011. This survey documents village-level characteristics related to housing and environment, population and labor force, socio-culture, land use, health and health facilities, sources of income and the village economy. Predominantly fisher villages ($n = 2098$) have been selected from the 2000 and 2008 PODES, 78% of the fisher villages rely on wild capture fisheries. The fisher

villages that are coastal and have wild capture fisheries ($n = 1590$), and a complete dataset of ($n = 1279$) villages. The welfare measure is the total number of malnutrition cases in each village. The 2008 and 2011 PODES surveys report the absolute values for this measure. The 2000 survey has a categorical value for this measure. We use the distribution of malnutrition in the year 2008 to estimate absolute values of malnutrition in PODES villages. Poverty levels are defined as number of households in slum areas (See Figure 4.1).

The environmental data have been collected from various GIS databases. Proxies for water quality are forest loss, aquatic chlorophyll-a concentrations in the water and degree heating weeks. The NOAA Coral Reef Watch SST products, such as the heating stress index (HIS) and degree heating weeks (DHW), indicate coral reefs that are undergoing heat stress. However, regions that are degraded due to pollution are more likely to be susceptible to bleaching (Thompson, Schroeder, Brando, & Schaffelke, 2014). Therefore, pollution, land degradation and deforestation will be used as proxies for degraded coastal environments. The interaction effect of heat stress and pollution will be used as the proxy for assigning pollution or stress treatment and control groups.

Forest cover change was obtained from the Global Forest Change map (Hansen et al., 2013). It is a time-series analysis of Landsat images characterizing forest extent and change. Forest loss was obtained at the *desa* level by overlaying the spatial location of the *desa*. Reef level threat data were obtained from the Reefs at Risk model, by the World Resources Institute. The local threats are a composite of coastal development, watershed-based pollution, marine-based pollution and damage, overfishing and destructive fishing. The global threats are a composite of thermal stress (warming sea temperatures, which can induce coral bleaching), and ocean acidification (driven by increased CO_2, which can reduce coral growth rates). Global and local threats have been modeled at the level of the reef. Further details on methodology can be obtained from the technical documentation (L. Burke

& Reytar, 2011). The geo-referenced reefs in the Reefs at Risk database were linked to the geo-referenced fisher villages by creating $30km$ buffers around each reefs. If a reef buffer overlapped a coastal village, it was included as part of the villages coastal resource. The reefs local and global threat indices were averaged by village. Coral bleaching data for the 1998 coral bleaching event were obtained from ReefBase (Reef Base, 2017).The bleaching data is based on 4 km resolution coral bleaching incidences recorded through direct scientific observation and based on satellite derived estimates of sea surface temperature anomalies. The chlorophyll-a concentrations have been obtained from OceanColor Web, supported by the NASA Goddard Space Flight Center. Chlorophylla-a concentrations were acquired for the year 1998 to correspond with the coral bleaching event (NASA & OB.DAAC, 2014). All GIS layers were processed in ArcGIS (Environmental Systems Research Institute, 2011) to correspond to specific villages and merged into R Studio (RStudio Team, 2015) for statistical data analysis.

Table 4.1 provides a summary of reported cases of malnutrition disaggregated by fisher village-type. There is very little variation in malnutrition across fisher villages in Indonesia. Contrary to what the PODES rates in malnutrition suggest, there is higher malnutrition reported in non-fisher villages in IFLS villages. Recall that trends in anemia measured as (% $<$ 12g Hb/dl) children under the age of 5 in fisher households is 74%, and is 44% for children ages 5-10, compared to a national average of 69% and 37% respectively. One reason for this disparity could be that, non-fisher villages might have higher awareness about malnutrition, and therefore tend to report it. There are statistically significant differences between non-fisher communities and fisher communities in reported malnutrition. Reported malnutrition is higher in non-fisher villages.

Table 4.2 provides a summary of poverty indicators in fishing and non-fishing villages in 2000. These indicators suggest that poverty in coastal fisher villages is higher compared to

inland fisher villages and non-fisher villages.

Since the objective of this paper is to understand the key drivers of malnutrition in fisher villages, all further analysis will be done on specifically fisher communities. Table 4.3 gives a summary of local, thermal threats, forest loss and levels of chlorophyll a disaggregated by the different subsets of fisher communities. The full data set has all fisher villages, dominated by fisher activities, which can be disaggregated by the fisher villages that are primarily wild-capture, inland or coastal. Further, these subsets are not mutually exclusive, therefore there are wild-capture villages that are inland and coastal. Table table:1 also provides are summary of the key village level variables. Super-smoothers between malnutrition and thermal threats identify a non-linear quadratic relationship (Figure 4.1). An initial rise in thermal threats may at first glance be beneficial for the fisher villages, however, a continued rise in thermal threats may be associated with rising malnutrition cases. Even though this may seem like compelling evidence for a strong relationship, we need to account for confounding factors that may also be driving this trend. See Appendix for more plots.

Table 4.1: Malnutrition in Indonesian Villages (2008)- Reporting Mean and (Standard Errors)

(Yes = 1, No = 0)	All Fisher Communities	Coastal Wild Capture Fisher	Inland Fisher	Non Fisher Communities
Fraction of reported cases of Malnutrition in the past 3 years	0.287	0.302	0.313	0.318
	(0.459)	(0.459)	(0.464)	(0.466)
Mean number of reported Malnutrition cases in the past 3 years	8.06	8.06	7.22	7.41
	(25.4)	(25.4)	(22.4)	(23.1)
Difference between presence of Malnutrition non-fisher and fisher villages (Two-Sample t-test)	t = -3.7185	t = -1.5483	t = -1.9239	-
	df = 75408	df = 74196	df = 136930	-
	p-value = 0.0002005	p-value = 0.1215	p-value = 0.05437	-

Table 4.2: Key Village Indicators in Coastal and Inland Fisher Villages (2000) - Reporting Mean and (Standard Errors)

	In Land Fishing	Coastal Fishing	In Land Non Fishing	Coastal Non Fishing
Total Population	1,836.260	1,996.093	2,978.975	3,893.533
	(2,120.615)	(2,678.768)	(2,288.726)	(2,855.288)
Number of poor households	14.782	64.919	7.380	77.863
	(24.301)	(93.874)	(12.784)	(84.336)
Percentage of poor households	0.028	0.127	0.007	0.047
	(0.048)	(0.158)	(0.015)	(0.071)
Percentage of pre-welfare households[a]	0.521	0.264	0.503	0.284
	(0.559)	(0.282)	(0.570)	(0.289)
Peoples economic condition in general[b]	3.374	0.574	3.345	0.551
	(3.442)	(0.572)	(3.424)	(0.558)
Number of households received identification paper for poor family	17.823	51.045	38.820	131.681
	(30.222)	(131.734)	(29.089)	(126.027)
Number of households who received Social Safety Net	86.196	145.229	161.226	229.768
	(121.192)	(195.545)	(121.867)	(197.219)
Location of village relative to a forest area[c]	2.706	0.539	2.650	0.603
	(2.722)	(0.479)	(2.656)	(0.519)

[a]Government programs tend to target poor areas and poor households. Here, poor areas tend to constitute IDT villages while poor families are considered to be pre-welfare according to BKKBN criteria. However, whether these categories are appropriate can also be questioned

[b]Economic condition defined as follows: 1 = very rich, 2 = rich, 3 = sufficient, 4 = poor, 5 = very poor

[c]Location defined as follows: 1 = Inside, 2 = Border, 3 = Outside

Table 4.3: Environmental Degradation Index (Local, Thermal, Forest Loss, Chlorophylla Concentrations) at the Village Level - Reporting Mean and (Standard Errors)

	(1) All Fisher Communities	(2) Wild Capture	(3) Coastal and Wild Capture	(4) Inland Fisher Communities
Thermal Threat Index	742.294	762.605	766.562	681.043
	(584.890)	(587.556)	(589.285)	(571.232)
Local Threat Index	982.273	938.443	929.370	1221.501
	(434.835)	(438.780)	(439.087)	(362.929)
Average Chlorophyll a Concentration in 2008 (mg/l)	1.734	1.741	1.762	1.066
	(3.878)	(3.642)	(3.703)	(2.131)
Forest Loss Index (units/area)	0.0491	0.0550	0.0532	0.0422
	(0.097)	(0.105)	(0.099)	(0.114)

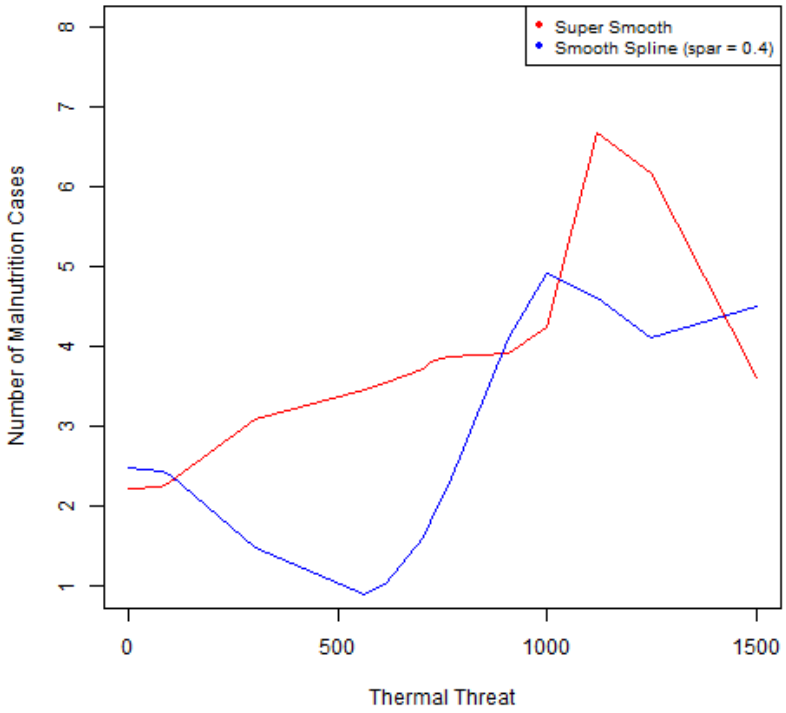

Figure 4.1: Malnutrition Cases and Thermal threats in predominantly fisher villages (PODES 2008)

Table 4.4: Key Fisher Village Variables

Statistic	Mean	St. Dev.	Min	Max
Number of malnutrition cases (past 3 years)	2.452	14.927	0	417
Villages with reported cases of malnutrition	0.325	0.469	0	1
Water pollution	0.110	0.313	0	1
Soilpollution	0.017	0.128	0	1
Presence of Electricity	0.996	0.063	0	1
Presence of Toilets	2.486	1.434	1	4
Number of places of worship	5.495	8.356	0	100
Presence of boats	0.003	0.058	0	1
Presence of motorboat	0.260	0.439	0	1
Rice land (ha)	14.048	61.527	0.000	740.000
Agriculture Production Kiosks	0.391	1.554	0	33
Fish drop off points	0.066	0.248	0	1
Fish Auction points	0.041	0.197	0	1
% of houses with telephones	0.007	0.020	0.000	0.199
% of houses with electricity	0.184	0.100	0.000	1.000
% of hospitals	0.002	0.002	0.000	0.017
% of schools	0.002	0.002	0.000	0.014
Total Population	2,149.535	2,690.582	79	47,084
Land converted to non-agriculture	0.242	0.429	0	1
Number of medical. persona	5.595	5.561	0	70
Death from measles	0.010	0.244	0	9
Number of cases of measles	0.710	4.840	0	98
Death from dengue	0.034	0.278	0	6
Number of cases of dengue	0.963	4.835	0	97
Death from avian flu	0.034	0.360	0	10
Number of cases of avian flu	3.902	16.270	0	98
Death from diarrhoea	0.103	0.609	0	10
Number of cases of diarrhoea	4.320	13.724	0	98
Number of crimes	21.481	0.865	16	22
% of farmer households	74.773	21.783	15	99
Wild capture fishery	0.788	0.409	0	1
Coastal fishery	0.879	0.326	0	1

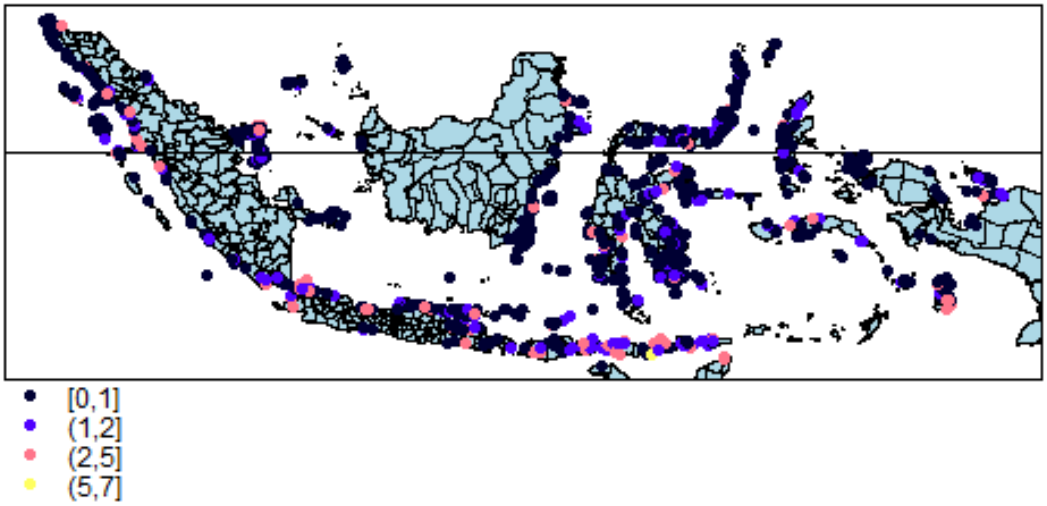

Figure 4.2: Distribution of log(malnutrition) cases in coastal wild capture fisher villages in Indonesia (2008)

4.6 Results - Spatial Trends in Malnutrition

Both forward and backward regressions converged to the same set of covariates. The motor-boat and fish-auction place covariates were not included after the optimal stepwise model was selected. We do not include these two covariates despite their theoretical significance in the literature. The linear model was used to determine the scope of the covariates through the step-wise model.

Thermal and local threats and *log*(number of malnutrition cases) appear to be spatially related (Table 4.5). The full sample is disaggregated by wild-capture, coastal wild-capture and inland fisheries. Although our main focus was to observe the coefficients on wild-capture coastal villages, we included the remaining villages as a falsification test. Indicators of local threats are disaggregated by the nature of the threat[4]. The coefficient on the interaction variable between thermal and overfishing and destructive fishing for wild-capture fishing villages is 2.0, which means that the incidence of thermal threat in regions with high local threats will increase malnutrition by 7 % points. This estimate accounts for the bias-correction in the log-normal distribution[5]. As expected local and threats are not significant for inland villages. Coastal threats are marginally significant. The control variables for natural capital in general have the expected signs, all of which are statistically significant. Villages with higher local or global thermal threats have higher cases of malnutrition. The coefficients of human capital also have the expected signs and are statistically significant. Lower percentage of households with electricity, hospitals, and schools are expected to have higher cases

[4]According to L. Burke and Reytar (2011), local threats are the greatest driver of increased pressure on reefs. The threat from overfishing and destructive fishing accounts for 80% of the local threats in the Indian Ocean regions. The threat from overfishing and destructive fishing can be largely attributed to the increase in coastal population pressure situated near the reefs. Reefs are also subject to pressure from coastal development, watershed-based pollution, and marine-based pollution particularly since 1998

[5]Bias correction for the log-normal distribution: $log(y) = \mu, E(y) = exp(\mu + \frac{\sigma^2}{2})$

of malnutrition.

Villages with higher incidence of malnutrition are also located in remote regions where deforestation rates are lower and chlorophyll a levels of the water body are lower. An increase in land conversion to non-agricultural land (urbanization) results in an increase in malnutrition. There are similar signs for the number of families that are receiving poverty insurance, and the number of measles incidences. You would expect that a more cooperatives (including formal and informal credit systems) would be negatively associated with incidences for malnutrition, however, we see that the relationship is counter intuitive. Social disruption and crime incidences are also lower in remote villages with high malnutrition rates. The coefficient on the thermal and local threats is statistically significant for coastal wild-capture fishing villages. The interaction effect of thermal and local threats, and the individual threats are not significant for inland villages. The spatial model also validates the significant difference between log malnutrition in coastal fisher and non-coastal fisher villages.

The coefficient on chlorophyll-a indicates that wild capture fisher communities are in relatively remote areas, where the waters are clear. The coefficients for houses with electricity (%), schools (%) land conversion to non-agriculture, measles incidences, crime and number of cooperative institutions are consistent with the linear model and the signs are as expected.

The falsification test is used to help determine whether the alternative population, namely, inland fishers, are affected by the potential confounders. We see that the interaction effects of local and thermal threats are not statistically significantly correlated with malnutrition in inland fisher villages.

Based on the results of a stepwise model, the interaction effects of overfishing, destructive fishing and thermal threats, coastal and thermal threats, water pollution and thermal threats are statistically significant local threats that are correlated with malnutrition in wild-capture

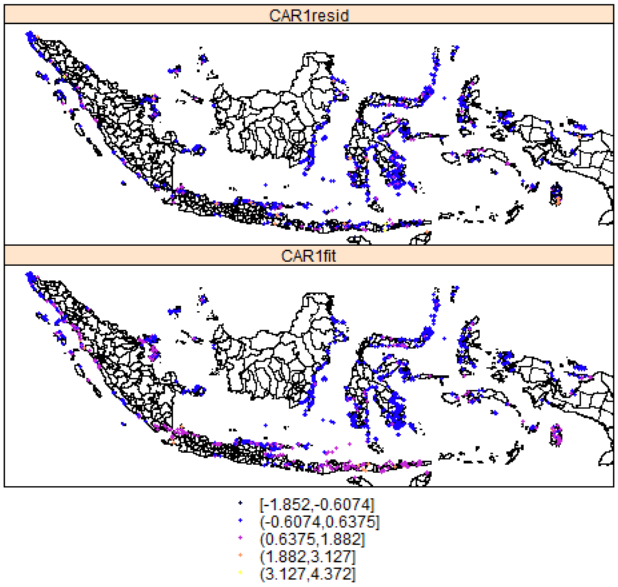

Figure 4.3: Residuals and Fitted Values of log(malnutrition) from the CAR specification

fisher villages. The results are also robust to the inclusion of a range of village level control variables that are known to impact incidences of malnutrition at the village level.

Table 4.5: Spatial Model: Determinants of Malnutrition in Fisher Communities- Reporting β, (standard errors), and significance levels ($*$)

	(1) Full	(2) Wild Capture	(3) Coastal Wild Capture	(4) Inland
Capital Assets				
Toilet	0.05***	0.051***	0.053***	-0.004
	(0.015)	(0.017)	(0.018)	(0.045)
Rice Land (Ha)	-0.001	0	-0.001	-0.001**
	(0)	(0)	(0.001)	(0.001)
Electricity(%)	-0.721***	-0.588***	-0.541***	-2.274***
	(0.217)	0.241	0.252	0.684
Hospital(%)	-29.57***	-36.143***	-35.545***	1.592
	(11.912)	(13.355)	(14.559)	(29.125)
Human Assets				
Schools(%)	-30.619***	-37.15***	-45.083***	30.503
	(12.791)	(14.946)	(15.997)	(31.956)
Land Conversion to non-Agriculture	0.146***	0.12**	0.123**	0.163
	(0.047)	(0.056)	(0.059)	(0.123)
Number of Cooperatives	0.035***	0.033***	0.033***	0.018
	(0.013)	(0.014)	(0.014)	(0.048)
Number of Measles Incidences	0.014***	0.015***	0.016***	0.003
	(0.004)	(0.004)	(0.004)	(0.013)
Natural Assets				
Chlorophyll-a 2008	-0.016***	-0.017***	-0.017***	0.004
	(0.006)	(0.007)	(0.007)	(0.027)
Water Pollution	0.142**	0.18***	0.2***	0.021
	(0.065)	(0.075)	(0.079)	(0.183)
Soil Pollution	0.345**	0.438***	0.422***	-0.06
	(0.158)	(0.176)	(0.179)	(0.567)
Log(Forest Loss)^3	0***	-0.001***	-0.001**	0
	(0)	(0)	(0)	(0)
(Destructive Fishing x Thermal Threat)^3	1.871**	2.176***	2.008**	0.679
	(0.883)	(0.9)	(0.902)	(0.854)
(Marine x Thermal Threat)	2.134	1.595	1.055	1.74
	(0.885)	(0.915)	(0.916)	(0.821)
(Coastal x Thermal Threat)	0.268**	0.285**	-0.181	1.4*
	(0.884)	(0.907)	(0.904)	(0.79)
(Water Pollution x Thermal Threat)^2	1.319**	1.455**	1.43*	0.89
	(0.826)	(0.856)	(0.853)	(0.776)
Lambda	318.227	173.077	266.656	66.188
LR test Value	49.686	37.939	44.606	5.974
Lambda p-value	1.8e-12	7.3e-10	2.41e-11	1.45e-02
Numerical Hessian SE of lambda	8.979	6.123	10.469	12.907
Log likelihood	-2117.285	-1714.362	-1582.026	-236.493
ML residual Variance	0.656	0.701	0.688	0.544
Observations	1749	1379	1279	211
Parameters estimated	28	28	28	28
AIC	4290.571	3484.724	3220.052	528.987

Note:*p<0.1; **p<0.05; ***p<0.01

4.7 Discussion

A consistent negative relationship exists between observed environmental threats and key socioeconomic indicators to malnutrition. There is a statistically significant negative association between schooling, incidence of diseases, presence of crime, forest loss and distance to main cities and malnutrition.

4.7.1 Natural Assets

The main research question was to test for a significant association between environmental degradation a key indicator for well-being, namely malnutrition. The results indicate that there is a positive and statistically significant relationship between the interaction of coral bleaching and water pollution on our indicator of well-being, malnutrition at the aggregated village level. After the inclusion of spatial effects, the coefficient on the interaction variable of thermal threats and the proxies for water pollution (forest loss, chlorophyll a, and water pollution reports) were significant. The results for coefficients on local and global threats and forest loss were significant. Destructive fishing was the most significant local threat, while forest loss was negatively associated with log(malnutrition). The interaction effects of destructive fishing and thermal threats were also significant. One obvious reason for these significant results is that overfishing and excess nutrient loads reduce the resilience and recovery of corals following acute climate change driven disturbances such as bleaching events (Hughes et al., 2003). These results are consistent with the theory that local water quality (physical and chemical) interacts with heat stress to degrade coral communities. In addition, eutrophication, nutrient enrichment, increased sedimentation and chemical toxins also degrade coral communities. We would expect forest loss to be positively correlated with

malnutrition, given that forest loss and forest fires result in degradation of water resources (Kim, Knowles, Manley, & Radoias, 2017). We do not observe this relationship primarily because the majority of the fisher villages are situated outside forested areas in coastal villages. Therefore, we observe a negative relationship between malnutrition and forest loss because poor water quality in fisher villages is not driven by forest loss.

An interesting finding from this research is that overfishing and destructive fishing practices were identified as the best indicators for local threats that were associated with fisher well-being (L. Pet-Soede & Erdmann, 1998). The interaction of thermal threats and destructive fishing practices are also significantly associated with malnutrition. Destructive fishing practices are prevalent in remote regions of the country, and are often the result of exploitation by strong sea-faring fishers. There are some ethnic groups that travel many kilometers in search of under-exploited remote reefs systems. Mobility of these fisher groups enables them to unsustainably extract resources in distant waters, away from their own home lands reef systems. They seldom have to face the consequences of reef degradation once it is rendered unproductive (L. Pet-Soede & Erdmann, 1998). The secondary objective of this research was to identify other key determinants of malnutrition in fisher communities. Although we have utilized all the publicly available data to understand the relationship between malnutrition and environmental degradation, we cannot overlook the gaps in current data. We have shown that the indices for local and thermal effects are consistent and statistically significant to all the robustness checks. The only challenge with these indices is that despite these robustness checks we cannot statistically claim causality between thermal and local threats and malnutrition in fisher villages. An omitted variable in our analysis is a proxy for the presence of sea grasses. Sea grasses are known to ameliorate seawater pollution from human-origination bacteria present in terrestrial effluent (Lamb et al., 2017). Furthermore, missing data such as declining fish catch per unit effort, number of fishers, or household income from wild capture

fishers could possibly give further insight into the causal chain. Further, data about the number of fish sold at fish auction location is available, but not at the village-level. Therefore, it is challenging to get a clear reflection of the changes in total catches within villages due to the interacting effects of water pollution and coral bleaching. The comprehensive catch and effort data is available with the Indonesian Directorate General of Fisheries (DGF). Without access to catch and effort data at the village aggregate, we cannot demonstrate how the relationship between coral bleaching and water pollution leads a lagged effect on the health of fisheries (Graham et al., 2007). We have not accounted for the province-specific differences in traditional or non-traditional fishing-practices, for example blast-fishing in the Spermonde Archipelago and dermal fishing in North Sumatra (Verité, 2012). Neither have we been able to show that land use land cover change influences water pollution levels. Our research does not capture these differences explicitly, except in the error variance of the spatial models. Exploration of these data sources merits further investigation. From the results of this study we can provide evidence to indicate that thermal threats in regions with poor water quality conditions and the existence of local threats (Thompson et al., 2014) have a statistically significant influence on well-being outcomes such as malnutrition.

4.7.2 Human Labor Assets

Local and thermal threats are not the only factors that are related to poor health outcomes; socioeconomic factors such as human and capital assets are important with respect to income generation and food consumption (Fiorella et al., 2014; Jalan & Ravallion, 2002). Significant associations between relevant human labor assets, such as education, health, schooling and their relationship to malnutrition were also examined. Based on the results (Table 4.5), the number of schools and hospitals is negatively associated with malnutrition. Health indicators

such as incidence of measles are positively correlated with malnutrition. These results are consistent with the literature that has already established that human assets such as level of education, health and schooling are key indicators of well-being (Duflo, 2000; Fiorella et al., 2014; Lanjouw & Pradhan, n.d.; Stanford et al., 2013). Declining incomes from fishing, push populations out of remote fisher villages, where as better job prospects and improved access to health care and educational facilities in urban areas are the drivers of rural to urban migration. These results are also consistent with previous studies that attribute out-migration in fisher villages for income opportunities in urban regions to declining employment in fisheries driven by environmental degradation or over-exploitation (Yuerlita et al., 2013).

However, we do have some findings that seem inconsistent with other literature. The coefficient on the proxy for remoteness is significant and inversely related to malnutrition cases. The coefficient on distance to city is not significant, and is also inversely related to malnutrition. This is counter to what some research on remoteness in fisher villages suggests (Salagrama, 2006). Geographic isolation can also result in poor health and educational infrastructure. The inverse relationship with remoteness and lower cases of reported malnutrition is suggesting that isolated fisher villages are better off. One reason could be that isolated villages are less accessible to commercial fishing or over-exploitation driven by global and local markets. The results indicate that reduced crime rates have a negative association with malnutrition. One reason could be that fisher villages have lower crime rates due to lower population, isolation from larger cities, more homogeneously equitable income distribution and higher levels of communal interdependence. Results suggest that lower crime rates are related to lower malnutrition incidences. Another plausible reason could be that low crime rates are a good proxy for social capital. There is evidence to suggest that social capital plays an important role in improving livelihoods of fisher communities (Stanford et al., 2014). It is still unclear how that would translate to lower malnutrition rates. Social

capital can be seen as a precursor to a successfully managed resource. However, even if the local community collaborates to manage its resource and has high evidence of social capital, beyond the designated four miles local artisanal fishers have to compete with large scale commercial fishing operations for a limited pool of natural resource (Prescott, Riwu, Steenbergen, & Stacey, 2015). To that point, commercial fishing operators have the advantage of better capital assets compared to the artisanal fishers. This emphasizes the fact that capital assets, such as motor boats, rice land, and access to credit systems are also relevant for income generation and food consumption and therefore influence the nutritional status of fisher families.

4.7.3 Capital Assets

Significant associations between relevant capital assets and malnutrition at the village level were also explored. We were expecting capital assets, such as motor boats, and hectares of rice land to have a negative, statistically significant correlation with malnutrition at the village level. We also expected the access to credit systems to have a negative association with malnutrition, given the assumption that access to credit improves the ability to generate income and buffer any unforeseen losses.

The results indicate that the presence of motorized boats in fishing villages is not an important determinant. Despite our results we rely on the literature and support the collective findings that motorization increases the number of locations and distances small-scale fishers can travel to harvest fish (C. Pet-Soede et al., 2001). Motorization also increases the adaptive capacity of fishers especially when local resources are either over exploited or degraded due to local and global threats (McClenachan et al., 2015; C. Pet-Soede et al., 2001). Increased access to viable fishing locations (Soselisa, 2004) increases income generating op-

portunities (Collier et al., 1977; Ferrol-Schulte et al., 2015; C. Pet-Soede et al., 2001). Our results are misleading because the data in PODES currently has a binary variable indicating whether the predominant mode of transportation is unmotorized boat or motorized boats or both. This is not as informative as it could have been, and is another reason why the results do not indicate statistical significance between the presence of motorized and unmotorized boats and malnutrition. In addition, there are other market driven mechanisms that could potentially be over-riding the effect of the motorboats. These could include, access to credit systems, access to markets and an imbalance of power relations between traders (who could be operating like a monopoly in distant villages) and fishers (Kwame Sundaram, 1991). Most interventions focus on improving fishing gear, motorization and processing equipment. These capital assets are important for small boat owners, but do not benefit the non-boats owners, therefore knowledge about the percentage of boat owners to non-boat owners can be an important determinant of well-being. This clearly suggests that data on the number of boats within the village is important to measure. Another reason why additional information on the number of motorized boats, boats and the nature of ownership is important is that, ownership of a motorized boat could potentially be a good proxy for the degree of fishing pressure and resultant impoverishment of small-artisanal fishers. If anything, we should have expected to see a positive relationship between motorboats and malnutrition. We know from the literature that outboard motor boats (pok-pok) have resulted in the disintegration of social institutions (such as the shared poverty institution) declining social capital and solidarity amongst fisher villages (Collier et al., 1977; Resosudarmo, Napitupulu, & Campbell, 2009; Soselisa, 2004). Indonesian operated vessels and foreign vessels, both illegal and commercial fishing activities have financial consequences for small-scale fishing communities. A mismanagement of biological capital leads to over-exploitation and rapid depletion of the fish stock by large motorized vessels operating illegally in inshore waters, often demarcated as traditional grounds for small-scale fishers. Consequently, there is an

increase in fishing effort (for example by resorting to blast fishing) in small-scale fishing communities who have been experiencing a decline in catch and lower earnings due to the illegal inshore fishing activities by large vessels. Therefore, economic development (motorized boats) (Collier et al., 1977) may result in more aggressive exploitation for short-term subsistence needs at the expense of long term conservation (Soselisa, 2004). Another reason for an inconclusive result could be that motorization facilitated a breakdown of local customs and their relevance in sustainably managing resources. In some regions of Indonesia motorization of vessels has resulted in a decline in the traditional conservation time (*sasi*), where fishers were not permitted to harvest fish in certain seasons (operating like a closed season) (Soselisa, 2004). Knowledge about boat ownership is also very important. Fishers who do not own boats, provide their labor and bear the risk of fishing trips in return for a share of profits. The bulk of the profits accrues to boat owners and middle men who control the fish trade (Collier et al., 1977; Soselisa, 2004). Consequently, a vast majority of these fishermen live in "squalid crowed settlements, with little to none alternative job opportunities "(Fox et al., 2009). Unless there are efforts to improve enforcement of marine laws and regulations that clearly identify exclusive zones for artisanal fishers, a revival of traditional shared poverty institutions and community based management initiatives cannot be successfully implemented, fulfilling the dual objectives of poverty alleviation and sustainable resource management through protection of fishing grounds (Resosudarmo et al., 2009). The rise of motor powered boats and capital-intensive trawlers has reduced the returns to operations of small-artisanal fishers in sail boats. Once we do measure the determinants associated with boats and motorboat ownership we may expect to identify a negative correlation between motorization and well-being in fisher villages. For now, however, our results on the magnitude and direction of the coefficients for motorboats is inconclusive. The number of cooperatives within the village is a proxy for the presence of credit systems. The availability of credit is expected to have a negative relationship with malnutrition. In a vast majority of

the cases middle men provide credit to impoverished fishers. Credit advances through the middlemen are used to supply fish to inland markets and by-passing bureaucratic red-tape for institutional credit and loans. This system is a mutually beneficial arrangement which enables fishers to buffer seasonal variations in income, but also ties them to wholesalers via credit bonds (Kwame Sundaram, 1991). The results are inconclusive primarily due to lack of detailed information regarding this interaction between fishers and middlemen. Results indicate that there is a positive association between land conversion to non-agricultural land with malnutrition. This is consistent with the social-ecological understanding of dependence on local natural resources. Increased diversification of sources of livelihoods is expected to reduce dependence on local natural resources (Mc Clanahan et al., 2008). The results also indicate that a decrease in rice lands increases cases of malnutrition. These results are also consistent with previous research that concludes that fisher communities are predominantly dependent on crop farming (Yuerlita et al., 2013) and that both sectors have higher incidence of poverty, and low levels of nutrition. These results indicate that a reduction in agricultural land and conversion to non-agricultural land is further marginalizing fisher communities and hence there is a positive and statistically significant association with malnutrition. Yuerlita et al. (2013) classified fisher households as "farming fishers ", "fishing farmers "and "mainly fishers ", based on their distinct livelihood characteristics. This research focuses on fishing farmers and mainly fishers at the village level, since the survey data does not explicitly indicate secondary income sources of predominantly farming villages. The results of this paper are consistent with our conclusions regarding mainly fishers (Yuerlita et al., 2013). The results demonstrate that "fishers "are consistently poorer, with higher rates of malnutrition own little or no land and have a less diversified livelihood. When the resource declines rural to urban migration of fishers takes place in search of employment, especially when artisanal fishers have few alternative job opportunities (Collier et al., 1977). These fishers often get hired in the same industry, however as employed labor. There is no direct

evidence to generalize this claim. Based on the data the results are conclusive regarding environmental degradation, aspects of human and capital assets, and the relationship with well-being in fisher villages. The results from spatial models also indicate the relevance of neighborhood endowments; physical, human (Jalan & Ravallion, 2002) and natural capital and their correlation with malnutrition. These results are generalizable at the country level, especially those related to specific local and global threats, access to education, better health care, more efficient credit systems, proximity to large cities and alternative job opportunities such as agriculture and rice farming.

4.8 Conclusion

This paper presents one major research objective, which was to identify a correlation between environmental degradation and malnutrition in coastal wild-capture fisher communities. A second objective was to identify the key determinants of well-being in fisher communities. Using socioeconomic data and merging it with ecological datasets, this research has established a clear and statistically significant relationship between malnutrition and the spatially related human, capital and natural assets. Even though the cause of malnutrition is multi-faceted, an understanding of the key drivers of malnutrition in fisher communities is a good starting point for further investigating a causal relationship and eventually improving policy interventions. Based on our findings the key determinant of well-being (malnutrition) in fisher communities is the cumulative environmental degradation resulting from, overfishing, coastal development, and watershed and marine-based pollution, including global threats such as ocean warming. The most significant local threat is overfishing and destructive fishing practices occurring near remote fisher villages. Since the community model accounts for spatial effects, these effects cannot be attributed to endogenous effects of malnutrition. The

results also indicate that geographically, labor and capital assets are also relevant determinants of malnutrition. Any prospects of improving malnutrition rates in fisher communities will therefore depend on the ability of government, international environmental agencies and community organizations to overcome the tendency to focus primarily on capital or labor endowments. Our findings emphasize the importance of also considering the persistent threats to corals (local and thermal) which have important implications for current marine management interventions. It is widely recognized that local-scale stressors should be minimized as an intermediate means of offsetting increases in global scale stressors (Hughes et al., 2003). Based on a review of literature, it is well-established that marine resource management in Indonesia is mired with many challenges. Identifying the determinants of well-being in fisher communities may be a key insight into understanding why poverty and low well-being persists in fisher communities, especially communities that are predominantly reliant on coastal wild-capture fisheries. Our results indicate that external threats to fisher villages, from destructive fishing, overfishing and thermal threats have a significant relationship with low outcomes of well-being. The presence of motor boats gives fishers the ability to venture further out. These fishers have an advantage over local artisanal fishers who rely on fisheries that are closer to shore and are more reliant on the environment in the immediate vicinity of their village. In addition, the skills, local knowledge and manual labor of subsistence artisanal fishers is becoming antiquated in comparison to the sophisticated commercial fishing companies. The traditional social security and village level adaptation and coping mechanisms have been weakened subsequently. Therefore, well-being primarily relies on the health of the ecosystem and a smoothly functioning public service (hospitals, schools, credit systems, rule of law, access to information and markets), and welfare state policies (Fiorella et al., 2014). A degraded common pool resource, exposed to decades of over-use may have driven the ecosystem to a less desirable stable state followed by lower productivity levels. This is consistent with open-access systems and poorly governed regulated access systems.

The presence of social capital or social disruption may also be important in determining social cohesion within traditional fishing village (Salagrama, 2006). A more difficult question (one that I was unable to answer here given data limitations) is to ask whether these external threats to well-being are leading to geographically concentrated poverty traps with critical thresholds (Jalan & Ravallion, 2002). It is well-documented that fishing is a risky occupation (D. G. Johnson et al., 1994). High inter annual variability in catches and prices for many fisheries leads to variability in the income and high levels of financial risk derived by fishery participants. Fishers in general are above the welfare thresholds (a poverty line) in many countries (Béné, 2009). Fisher households are vulnerable to idiosyncratic shocks or natural disturbances (Allison & Horemans, 2006) that can potentially push them below the poverty threshold into persistent poverty traps (Carter & Barrett, 2006; Carter, Little, Mogues, & Negatu, 2007). We would expect that a fisher community with low levels of human and capital assets will find itself vulnerable to falling into poverty traps. Empirical evidence suggests that fishers are not necessarily trapped in chronic poverty. Coastal marine social ecological poverty traps arise when policy interventions do not adequately respond to all aspects of vulnerability, namely exposure, susceptibility, sensitivity, and adaptive capacity (Ferrol-Schulte et al., 2015).

Incidences of malnutrition in fisher households (percent of malnourished children under the age of five) can be an important social-ecological indicator of a critical threshold within a village, especially if fishers are unable to migrate or choose alternate livelihood. If measured periodically over time, then one is able to track the relationship between environmental shocks such as spatially exogenous thermal stressors, local stressors and malnutrition outcomes. If the cases of malnutrition within a village increase beyond a threshold following a climate driven depletion in the ecosystem that exhibits hysteretic and irreversible changes, then we can expect to see persistent poverty traps. Identification of social ecological poverty

traps can enable managers to identify tipping points within social ecological systems where resilience needs to be built such that communities do not cross those points and if so, have at their disposal short-term coping strategies and long-term institutionalized adaptation mechanisms to bounce back to the more socially favorable social ecological state. The reliance on natural capital (fisheries) as the major productive resource can result in persistent poverty traps owing to feedbacks from the natural resource and anthropogenic depredation, which is often challenged by exogenous environmental shocks (Barrett et al., 2016). Therefore, we can expect that the human induced degradation or climate-driven depletion of ecological community assets (such as fish stock) can result in poverty traps, as shown in (Toth, 2015).

Similar to poverty thresholds, social ecological systems contain non-convex thresholds that exhibit hysteretic and irreversible changes (Walker et al., 2002), that is, it is difficult to reverse the transition between alternate states. For example, the degradation of a marine ecosystem and a subsequent decline in well-being of communities in coastal settlements can move a social ecological system beyond a critical threshold where the system irreversibly enters a different state. In the alternate phase, fishers have either migrated to different coastal regions or have switched in different livelihood practices, abandoning livelihood dependence on the fishery.

The discussion of poverty traps and resilience analysis leads us to a discussion of the limitations of this paper. An analysis of poverty and welfare dynamics was beyond the scope of this paper. An analysis of a causal relationship between malnutrition and the multiple threats to the ecosystem was also beyond the scope of this paper. It would require a richer and more consistent set of annual (or periodic) data that could be directly linked to the cyclical patterns in natural resources. In addition, a systematic randomized experiment would enable a further discussion on causality. As mentioned earlier, there were only two consistent data points (2008, 2011) for malnutrition data in the PODES. Therefore, a poverty

dynamics study will have to rely on multiple periodic survey data, preferably at the level of fisher household. Such data would also enable us to study the well-being to natural resource conditions at birth on adult fisher health, and outcomes similar to empirically robust studies (Maccini & Yang, 2009).

Such research in conjunction with the focus on social and ecological poverty traps can help us better understand the linkages and causal connections between the health of the environment and the health outcomes in resource dependent artisanal fisher communities. Understanding these linkages and causal relationships can help policy makers identify theories of change, which will enable implementation agencies to address the dual objectives of poverty alleviation in a global commons.

CHAPTER 5

CONCLUSION

This dissertation has explored empirical questions associated with natural and anthropogenic disturbances in ecosystems that support viable populations of fish species with commercial and recreational value. Given the spatial nature of the problems, each empirical question was addressed by developing appropriate spatial models. In Chapter 2: Identifying the impact of spatial oceanographic anomalies (sea surface temperature) on summer flounder *(Paralichthys dentatus)* in the U.S. Mid-Atlantic Bight, I explore whether there is a northward shift in the distribution of the summer flounder in response to regional climate driven increase in ocean temperature. I also test whether the localized spatial pattern of abundance is driven by temperature and other environmental factors. A Bayesian spatial-temporal model is applied to the summer flounder abundance data. In our preliminary linear analysis (See Appendix) we find that maximum ocean surface temperature, depth, and latitude are the most important predictors of fish presence. Our results from the spatial-temporal models consistently reveal that latitude, temperature, and depth are statistically significant. The spatial-temporal models have spatially structured and unstructured effects, temporally structured and unstructured effect. The model with the lowest DIC has a temporal unstructured random effect, along with structured and unstructured spatial effects, Model 4. Model 6 also has a DIC close to Model 4. Model 6 has spatial and temporal interaction, indicating that spatial and temporal variation is inseperable in the incidence of summer flounder in the Mid-Atlantic Bight. The Fall abundance is explained by BT, SST and salinity. The Spring abundance is explained by BT and salinity. Therefore, our results reveal that temperature is important in driving the spatial location of summer flounder, especially within the Gulf of Maine, during warmer years. However, the quantity of fish is consistently low (Terceiro, 2006). One plausible explanation is that deeper waters in the Gulf of Maine, and the off-

shore habitat off the Gulf of Maine may not be a suitable habitat for the summer flounder. Overall this exercise has given us considerable insight into predicting whether we can expect to see the summer flounder in the Gulf of Maine under warming ocean temperatures. We also compared the accuracy of the estimates from the R-INLA to the CAR in spdep. The coefficients are comparable, eventhough the spdep and INLA packages use different CAR models.

In Chapter 3: Pure Open Access and Spatial Management in a Two-Zone Fishery, I explore the ecosystem dynamics of the whether the Maine coastal ecosystem supports two stable steady states, one with high urchin biomass (low kelp and crab biomass), and one with low urchin biomass (high kelp and crab biomass). The objective is to determine whether over-harvesting in the Maine green sea urchin fishery may have "flipped "the ecosystem into an economically less desirable equilibrium. I develop three models calibrated to the Maine green sea urchin fishery *circa* 1995. These three models test the system dynamics that have led to a decline in this fishery. The first model is a two-zone, pure open access model, with larval dispersion representing a four-dimensional dynamic system. The extinction steady state is locally stable, while the non-extinction steady state is locally stable, exhibiting spiral convergence. Both Zones 1 and 2 decline to 20% and 30% of their carrying capacity in the non-extinction steady state. The second model is a two-zone, pure open access model, with larval dispersion with an objective function tracking Hunter (2015) biomass estimates. Varying E_i results in a non-stationary, non-steady state model. The third model is a dynamic mixed integer model that maximizes the present value of net revenue. This model is used to test whether periodic closure of Zones 1 or 2 would be optimal to permit stocks to rebuild, or whether the creation of a marine reserve would be optimal. The model is able to optimally restrict E_i in both Zones, giving a net present value of approximately $386 million.

In Chapter 4: Marine Resource Degradation and Malnutrition. A Spatial Community

Model of Well-being in Small-scale Fisher Communities in Indonesia, I empirically identify a relationship between malnutrition in wild-capture artisanal fisher communities and environmental degradation around adjacent coral reefs. I extended the Cobb-Douglas production function to estimate village level malnutrition cases as a function of physical, human and natural capital. The assumption of this model is that a failure in either The physical, human and natural capital will result in the production of poverty. The Cobb-Douglas function is nested in the conditional auto-regressive model to account for spatial dependencies. Well-being in a particular village, is conditional on the well-being in neighboring villages. Socio-economic data is merged with reef specific ecological data at the village level. Key determinants of well-being (as measured in malnutrition cases) are over-fishing, coastal development, watershed and marine-based pollution, and ocean warming events that result in coral bleaching. Labor and capital assets are also significant determinants of malnutrition. The different institutional, and environmental causes of malnutrition are multi-faceted. It is difficult to develop a theory of change without demonstrating causality through a quasi-experiment. However, the results of this study indicate that the persistent threats to corals, from local-scale stressors may be interacting with global stressors to decrease fishing productivity in artisanal villages. The most significant threats to malnutrition are destructive fishing, over-fishing and thermal threats.

Open-access ecosystems and common pool resources are exposed to decades of over-use. If the system is gradually approaching a less desirable state, a stochastic environmental shock can easily flip the ecosystem to an unstable less desirable state. Social ecological systems contain nonconvex thresholds that exhibit hysterectic and irreversible changes (Walker et al., 2002). The results from Chapter 3 and Chapter 4 suggest that degradation of marine resources such as the urchin barrens, or the coral reefs may have resulted in the ecosystems shifting to a hysterectic alternate state. In the case of the green sea urchin, it will be unlikely

that the creation of marine protected areas, or reduction in harvesting will restore the fishery to its original carrying capacity. In the alternate state, fishers either migrate to different coastal regions, switch to alternate livelihood practices, or remain in geographically isolated poverty traps in the absence of social and institutional relief.

The three ecosystem that are covered in this dissertation all represent some aspect of these theories. The results of my studies suggest that all management decisions take into consideration a precautionary approach that takes into account stochastic environmental events. Policies should also focus on reducing local sources of anthropogenic stressors, given that regional scale policies are easier to implement with a higher chance of ameliorating and off-setting global climate change driven stressors.

APPENDIX A

SUMMER FLOUNDER

In the following analysis, we examine changes in the spatial distribution of the summer flounder (*Paralichthys dentates*) relative to sea surface temperature (SST), depth, season, and salinity for the years 1991-2015. We use various statistical models such as GAMS, KNN and trees to examine which variables correlate with fish absence and presence in the administrative regions off the East Coast, U.S.A. Fish abundance data were collected during National Marine Fisheries Service (NMFS) Spring and fall bottom trawl surveys. SST was derived from the Advanced Very High Resolution Radiometer Pathfinder SST time series (1985-2009) and the Aqua MODIS nighttime SST time series (2010-2015) as provided by NOAA's National Environmental Satellite, Data and Information Service. Previous research using trawl data through 2008 indicates that the summer flounder has exhibited a significant northward trend during the fall. Our estimation of the more recent time series data indicates that the northern shift in the distribution of the summer flounder stock is correlated with a regional-climate-driven increase in ocean temperature and that there is a change in the spatial patterns of presence in response to warm years. Our analysis of the Spring and Fall 1991-2015 data suggests that the effect of temperature on abundance is significant, especially in shallower waters of the Gulf of Maine.

The data cleaning process involved acquiring the SST data from the satellite NetCDF files by administrative region and matching them to the NMFS survey data by administrative region ID, Year, Season (processed in Python). This data was imported in R Statistical software for further data structuring and statistical modeling. The x and y coordinates are the centroids of each administrative region ID that are acquired from the Shapefile. The bathymetry is also the average depth across each region. The outcome variable is an index

of the number of fish found in each region by year and season. We simplified our data set to look at just 'presence' and 'absence' of summer flounder across each region by Year and Season.

A.1 Linear Regression

We began our linear regression analysis with the ridge and lasso regression. The ridge and lasso regressions were used to fit various models during the model exploration process. For each regularization model, we chose the tuning parameter that minimized the cross-validation error. We then compared the accuracy rate of each model under the ridge regression and lasso regression model. Since the accuracy rates for lasso regression were consistently higher than the ridge regression, we used the lasso regression model to select predictors. Under lasso regression, the accuracy of each model resulted in a rate between 72.7% and 80.1%. Across all models, the coefficients of predictors, depth and y, were generally larger than that of the other predictors. This suggests the depth and y variables have the most deterministic effect in the prediction. The model that yielded the highest accuracy rate had a rate of 80.1%. This model suggests that including second order variables, "$tempmax^2$ ", "BOTTEMP2 ", and interaction variable "$BOTTEMP \times tempmax^2$ "in addition to the original set of predictors contribute to the prediction of summer flounder presence as the model has the highest accuracy rate and none of the variable coefficients converge to zero. However, evaluating the coefficients, we see that among all the predictors, variables tempmax, depth, y and $BOTTEMP \times tempmax^2$ contribute the most to the prediction whereas variables latitude (x) and $tempmax^2$ have relatively insignificant effects on presence summer flounder than other predictors. (See Table reffig:A.T1)

Next we performed PCA before running the nonlinear models. Dimension reduction using the PCA reveals that some of the explanatory variables, such as Seasonal variation and Year, will not add any additional insight to our models. For example, the magnitude of Season and tempsd is small and they point in the same direction as tempmax. This reveals that removing Season and tempsd will decrease the variance in our estimates of the reduced model. (See Figure A.1)

A.2 Classification with Logistic Regression

In addition to linear models, we explored classification with the logistic regression models to see if they provide us more insights into predicting the presence of Fluke. The linear regression model assumes the response variable "fish "is quantitative. Our outcome variable "fish "is qualitative and falls into two categories, "presence "or "absence ". We used logistic regression to model the probability that our outcome variable belongs to either of these categories. We added polynomials to predictor variables to test if there are non-linear relationships in the data that may need to be accounted for. In order to determine what the optimal threshold to use as a cut off point for our model prediction, we first fit our data with polynomial models raised to powers ranging from 1 to 6. The results of cross-validation on training data and AIC were lowest for the model with the highest complexity. Based on the true positive rate and false positive rate from the result, we plotted the corresponding logistic regression test error. We found that the minimal test error results from the 6th degree polynomial model. However, a polynomial model with such a high degree is hard to interpret. Since a degree four polynomial still has a reasonable test error rate of 0.20 compared to a test error rate of 0.195 resulting from the 6th degree polynomial, we decided to use a degree four polynomial for computing the optimal threshold for reducing classification error

(See Table A.2). After graphing a Receiver Operating Characteristic curve (ROC curve), we observed that the optimal cut-off ranges from 0.35 to 0.4; we have a high proportion of true positives correctly identified.

Since a commercial goal of the research is to help management with reallocation of state commercial quotas, we hope to maximize prediction of the Fluke presence. We think it is more important to identify conditions indicating presence of Fluke and thus set the cut-off point to the higher end, which is 0.4. The resulting curve indicates that the optimal rate lies between 0.3 and 80.4 (Figure A.2). Choosing the latter extreme value yields an overall model classification accuracy rate of 0.814 ($\sim 82\%$). The results from these models suggest that there is non-linearity in the data that needs to be accounted for, thus making the case for more complex models.

Next, we fit a Generalized Additive Model (GAM) using smoothing splines in order to predict the probability that fish will be absent or present based on the nine predictors in our data (Figure A.3). The optimal effective degrees of freedom–and hence the flexibility of each smoothing spline were chosen to minimize the leave-one out cross-validation (LOOCV) error, and the resulting values are summarized in Table A.3. Note that a smoothing spline could not be fit to the predictor Season, since its range has less than 4 unique values.

We then created a GAM using smoothing splines with the cross-validated degrees of freedom, adding Season as a linear term. The fitted curves for each of the nine predictors are displayed in Figure A.3. Based on the outputs of this model, we observed that the function of the predictors Year and Season look rather linear and their relative contributions are small. This is consistent with results from the PCA. Thus, we ran a series of ANOVA tests to determine whether these predictors should be excluded or fit using a function of a different form (such as linear). We first performed an ANOVA to determine which of

the following three models is best: a GAM that excludes year, a GAM that uses a linear function of Year, and a GAM that uses a spline function of Year. Based on the output, there is compelling evidence that a GAM using a spline function with df = 2 is preferable to the other two alternatives ($p - value = 2.2e - 16$). The ROC Logistic Regression ANOVA test comparing the relative significance of including versus excluding Season is inconclusive. Therefore, we remove Season from our model to reduce its overall complexity.

We then produced a summary of the GAM fit using spline functions of all the remaining predictors. The small p-values for 8 predictors (summarized to the right) reinforce our conclusion from the ANOVA test that a spline function of Year is best suited for this model. Further, this confirms our belief that the true functions of the other 7 predictors in the model are in fact non-linear.

Lastly, the predictive accuracy of the GAM was assessed using the classification error rate. To determine the optimal classification threshold for our chosen model, we built an ROC curve displaying the trade-off between the True-Positive and False-Positive rates from 0 to 1. The resulting curve indicated that the optimal rate lies between 0.4 and 0.5. Choosing the latter extreme value yielded in an overall model classification accuracy rate of 0.846 ($\sim 85\%$). This ROC (Figure A.4)shows a significant improvement over the ROC generated from the linear model (Figure A.2). Analyzing the output of GAM points to a number of interesting conclusions. For instance, we see that of the 8 predictors used to fit our model, the 3 predictors with the largest contributions to the response value are tempmax, depth and y, as indicated by their vertical scale. Thus, these 3 variables have a much larger effect on the predicting the probability of Fluke presence than other predictors in our model (Figure A.5). This observation is consistent with the p-values obtained for each predictor in the previous summary of the GAM. Further, this model indicates that Fluke are more likely to be present in shallow waters and the probability of observing Fluke rapidly declines in the

north in the deeper waters of the Gulf of Maine.

K-Nearest Neighbors was also fit to the dataset as an attempt to further explore different nonlinear models. We used cross validation to compute the K-value that yields the lowest cross validation test error. A small value of K will provide a very flexible fit, with a low bias and high variance. In contrast, a larger value of K will give smoother predictions, a less variable fit, with a higher bias. Based on our cross-validation results, the K-value that will give the minimal cross validation is 1 (Figure A.6). However, as discussed earlier, a small k-value is characterized by very flexible fit. If we try to fit a model with K-value equal to 1 on a new dataset, it will give us a very inaccurate prediction. Therefore, we decided not to further explore the KNN model, as we want to develop a consistent model that is applicable to fitting different data.

In addition to the KNN classification model, a pruned decision tree, an un-pruned decision tree, a bagging tree, and a random forest that considers various numbers of predictors at each split of the tree were fitted on the dataset. The pruned and un-pruned tree models produced a training accuracy rate of around 83.7% and 84.4% respectively. Using cross validation, we found that a pruned tree with 8 terminal nodes will result in the lower cross validation error. We examined the structure of such tree and found that the most important indicator of fluke's presence is y as the first branch differentiates at value $y < 41.328$.The model also hypothesizes a few combinations of factors that lead to presence of fluke in a region. For example, if we are looking into a region with y-coordinate smaller than 41.33, maximum temperature greater than 7.54 degrees Celsius, and with $depth > 82$ meters, we should expect the presence of Fluke (Figure A.7).

However, even with the help of cross validation to pick the optimal number of terminal nodes, a single decision tree may subject to high variance and prone to over fit data.

Therefore, we proceeded to fit our data with a bagging tree and random forests. Based on the average of 500 trees, the bagging tree (Figure A.8) and random forests tree models gave a training accuracy rate ranges from 96.8% to 97.9% using the validation set approach. Since the random forest with 8 terminal nodes has a high accuracy rate of 97.6% and it was determined to be the tree with the lowest training error, we will continue considering this model for simplicity.

We examined the Mean Decrease Gini value of the tree and observed that variables y, tempmax, and depth are the top three most important factors and they most effectively decrease the tree node impurity by reducing the node variance. This complements the structure of the single tree model. The first split of the tree is dependent on variable y, while the two branches below the first split depend on either tempmax or depth.

A.3 Summary

The objective of this exercise was to determine the main determinants of fish presence/absence, especially with respect to the spatial location of the fish. Overall, in our analysis we find that tempmax, depth, and y are the most important predictors of fish presence. We tested different linear and nonlinear models to arrive at our main conclusions. The first set of regressions were run on a logistic regression model and our classification accuracy was $\sim 82\%$. We also learned that there was non-linearity in our data.

Next we performed the PCA and lasso regression models. We learned that Season, tempsd, and Year are not adding any additional insight into our models. The lasso regression revealed that depth and y have the greatest effect on model prediction and had an accuracy rate of 80.1%. We also tested our hypothesis by building GAMS using smoothing splines.

Our results reveal that Season has no effect, and that the most significant predictors are tempmax, depth and y. These variables have the greatest contribution to predicting the probability of fish. This is consistent with the results from the previous two models. The classification accuracy for the GAM was $\sim 85\%$, which is an improvement over the logistic regression polynomial fit. Next we explored using the KNN as another non-linear method to fit our data. However, the results of the KNN were largely inconclusive, given that the lowest test error rate is attained when $K = 1$. We did add random variation to the outcome variable to further understand this result; however, random variation did not change the optimal K value. This does give some insight about how our data may not follow the conventional groupings where we can build clear presence/absence non-linear boundaries.

We also used the decision trees to get an easily interpretable and visually self explanatory understanding of our data. We learned that a pruned tree with eight terminal nodes yields the lowest cross-validation error, with the most important predictors being y, tempmax and depth. Biologically this is accurate, given our understanding of the summer flounder fishery.

We also learned about the ideal temperature thresholds along with the interaction of depth. Therefore, we can expect to find the summer flounder in southern and central administrative regions (< 41.3 decimal degrees) with temperatures above 7.5 Celsius at a $depth > -82$ meters, during the Fall season. We will expect to see the summer flounder in the Gulf of Maine (northern latitudes) at $depth > -63 meters$ (which are the shallower regions of the Gulf), if the $tempmax > 17.4$ Celsius, during warmer years. This is a very important insight that addresses our hypothesis which was testing for whether the summer flounder can be expected in the Gulf of Maine, given warming SST (measured in tempmax) in the future owing to climate change. Our results reveal that we can expect to see the summer flounder if SST continues to increase in the Gulf of Maine. The pruned and un-pruned trees produced an accuracy of $\sim 84\%$. To further improve accuracy, we tested our data

with the bagging trees and random forests. This increased our training accuracy to $\sim 97\%$. Further we examined the mean Gini index which confirmed our previous findings that y, depth and tempmax are the three most important predictors of fish absence/ presence and most effectively decrease tree node impurity by reducing the node variance (based on the averaging to 500 trees).

The main questions this analysis sought to address were:

1. What are the ecological determinants of fish presence/absence. Our results consistently reveal that y, tempmax and depth are the most important. 2. Whether temperature and salinity are important predictors for spatial distribution.

Our results reveal that temperature is important in driving the spatial location of summer flounder, especially within the Gulf of Maine, during warmer years. Overall this exercise has given us considerable insight into predicting summer flounder presence in the Gulf of Maine given the effects of climate change.

Model Parameters	Ridge.accuracy	Ridge.coef	Lasso.accuracy	Lasso.coef
tempmax+tempsd+depth+BOTTEMP+BOTSALIN+x+y+Year+Season	0.7215	c(-0.3706, 0.3037, 0.3483, 0.8173, -0.05927, 0.03929, -0.2277, -0.5732, -0.7264, -0.1212)	0.7368	c(-0.3329, 0.8643, 0.3991, 1.348, -0.1913, 0.2302, -0.127, -0.5258, -0.5461, 0.1437)
tempmax+tempsd+depth+BOTTEMP+BOTSALIN+x+y+tempmax2+BOTTEMP2+BOTTEMPxtempmax2+Year	0.7418	c(-0.5941, 0.4381, 0.346, 0.8263, 0.135, 0.09177, -0.2525, -0.6816, 0.1843, 0.09749, -0.763, -0.7304)	0.801	c(-1.458, 2.075, 0.3521, 1.49, 0.01086, 0.3223, -0.03871, -1.192, 0.09879, 1.07, -2.841, -0.5057)
tempmax+tempsd+depth+BOTTEMP+BOTSALIN+x+y+tempsd2+tempmax2+tempmax2xtempsd2+Year	0.722	c(-0.592, 0.2312, 0.4442, 0.824, -0.04625, 0.0432, -0.2429, -0.6266, 0.001065, -0.1141, -0.1517, -0.7438)	0.7558	c(-1.56, 4.109, 0.7256, 1.379, -0.2115, 0.2904, -0.06471, -1.151, -0.5681, -4.027, 0.1703, -0.2286)
tempmax+tempsd+depth+BOTTEMP+BOTSALIN+x+y+tempsd2+BOTTEMP2+BOTTEMP2xtempsd2+Year	0.717	c(-0.5878, 0.1216, 0.4204, 0.8199, 0.005125, 0.05697, -0.2465, -0.6245, -0.08853, -0.07362, 0.0006528, -0.7305)	0.7357	c(-1.222, 0.06824, 0.9608, 1.339, 0.05089, 0.2406, -0.1874, -0.8154, -0.6209, -0.2474, 0.06503, -0.498)
tempmax+tempsd+depth+BOTTEMP+BOTSALIN+BOTSAL2+BOTTEMP2+BOTTEMPxBOTSAL+Year	0.7028	c(-0.615, 0.3143, 0.3264, 1.264, 0.1557, -0.04325, -0.04461, 0.03044, 0.1252)	0.7278	c(-1.296, 0.3048, 0.4413, 2.065, 0, -1.151, 1.239, -0.5198, 0.8325)

Table A.1: Ridge and Lasso Regression

	Model Parameters	CV.ERROR	AIC
Model 1	poly(tempmax, 6)	0.16	11154.08
Model 2	poly(tempmax, 6)+poly(tempsd, 6)	0.16	11081.65
Model 3	poly(tempmax, 6)+poly(tempsd, 6)+poly(depth, 6)	0.14	9845.25
Model 4	poly(tempmax, 6)+poly(tempsd, 6)+poly(depth, 6)+poly(BOTTEMP, 6)	0.14	9817.88
Model 5	poly(tempmax, 6)+poly(tempsd, 6)+poly(depth, 6)+poly(BOTTEMP, 6)+poly(BOTSALIN, 6)	0.14	9777.18
Model 6	poly(tempmax, 6)+poly(tempsd, 6)+poly(depth, 6)+poly(BOTTEMP, 6)+poly(BOTSALIN, 6)+poly(BOTTEMPSALIN) 6)	0.14	9779.12
Model 7	poly(tempmax, 6)+poly(tempsd, 6)+poly(depth, 6)+poly(BOTTEMP, 6)+poly(BOTSALIN, 6)+poly(BOTTEMPSALIN) 6)+x+y	0.14	9779.12
Model 8	poly(tempmax, 4)+poly(tempsd, 4)+poly(depth, 4)+poly(BOTTEMP, 4)+poly(BOTSALIN, 4)+poly(BOTTEMPSALIN) 4)+x+y+Year:poly(tempmax,) 4	0.13	9221.1
Model 9	poly(tempmax, 6)+poly(tempsd, 6)+poly(depth, 6)+poly(BOTTEMP, 6)+poly(BOTSALIN, 6)+poly(BOTTEMPSALIN) 6)+x+y+Year:poly(tempmax,) 6 + Season	0.12	8862.22

Table A.2: Summary: Logistic Regression

Predictor	Degrees of Freedom
tempmax	12.37
tempsd	6.23
depth	5.69
Year	2
BOTTEMP	13.23
BOTSALIN	22.52
x	21.95
y	7.62

Table A.3: Degrees of Freedom for Smoothing Spline in GAM

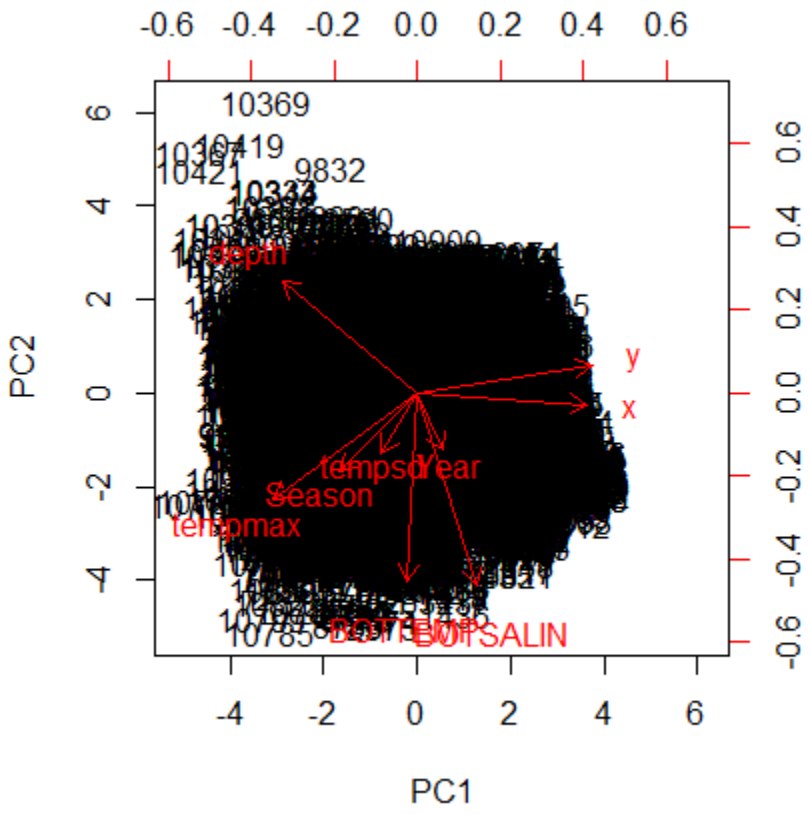

Figure A.1: Principal Component Analysis BiPlot

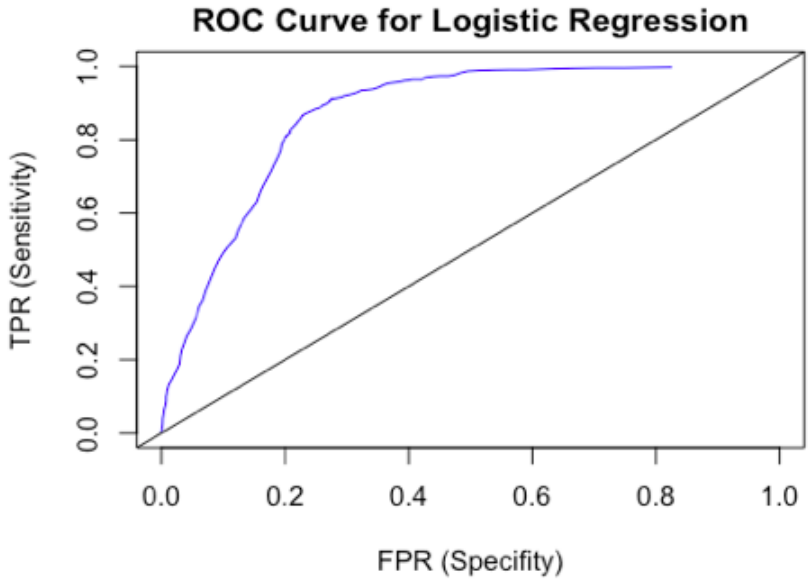

Figure A.2: ROC - Logistic Regression

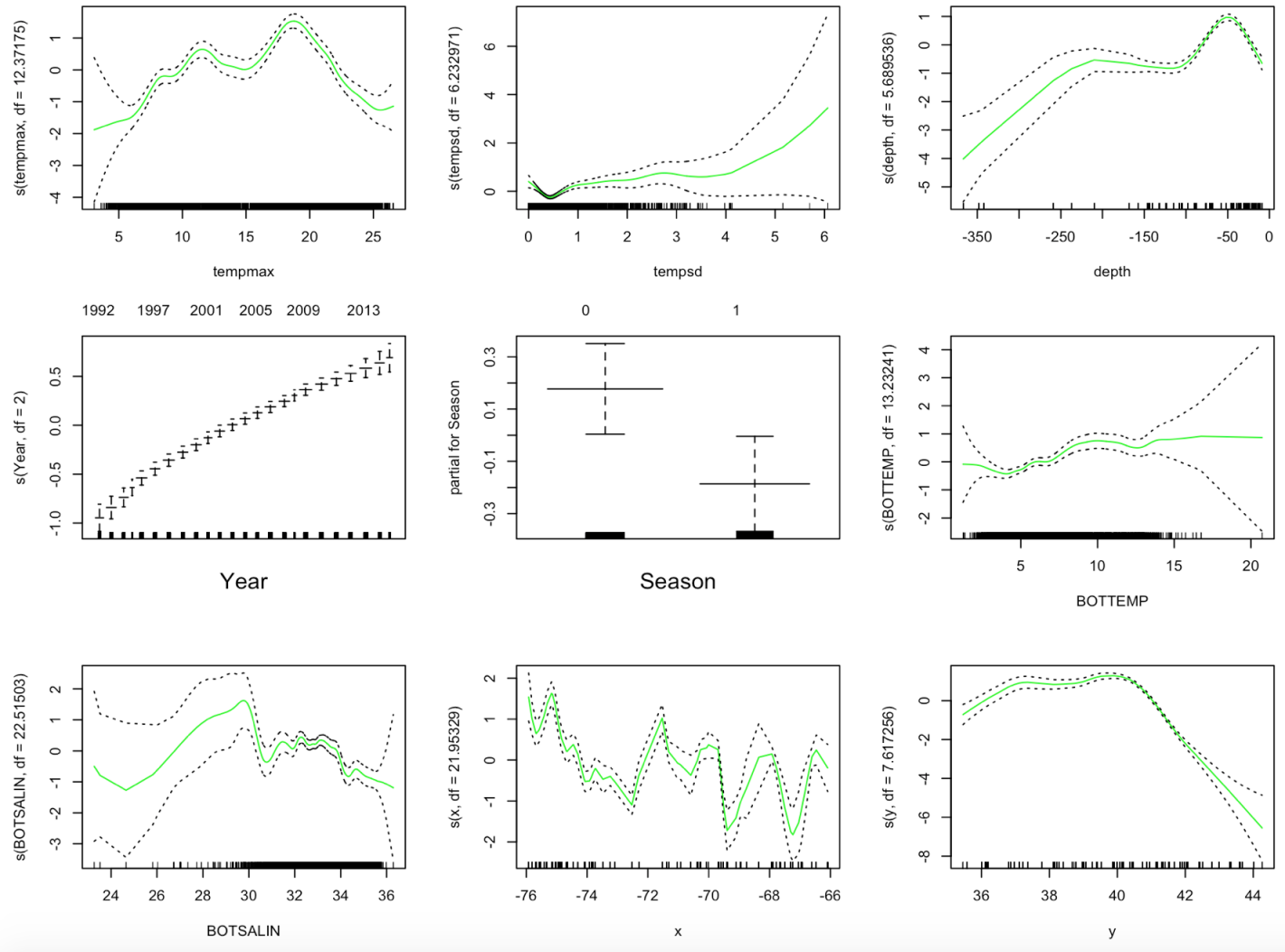

Figure A.3: Summary Results: GAM using smoothing splines with the cross-validated degrees of freedom

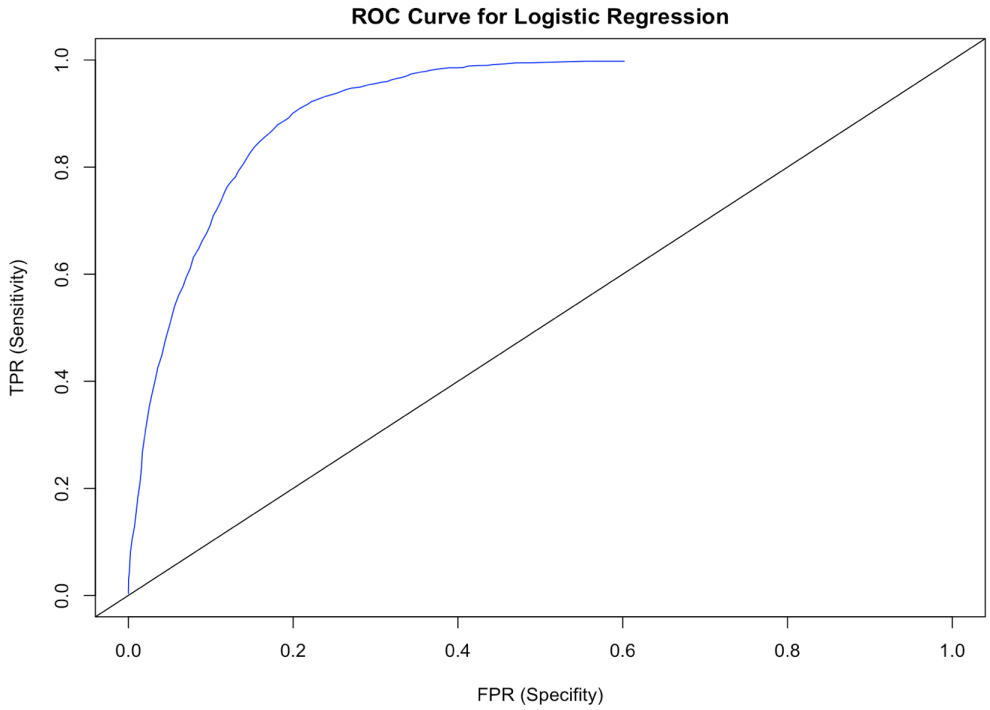

Figure A.4: ROC - GAM

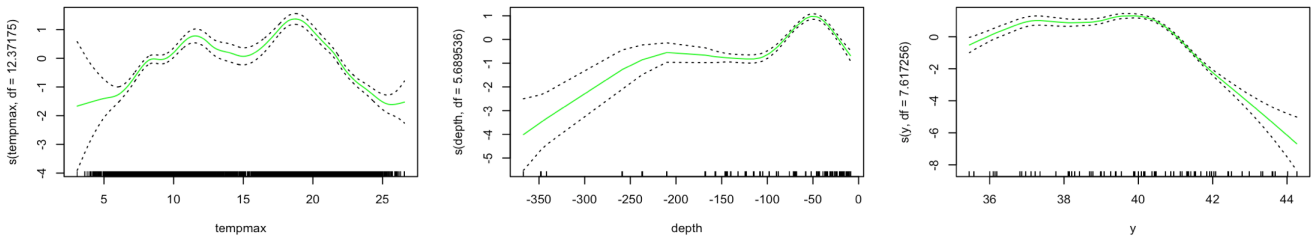

Figure A.5: Predictors with the largest contribution in the GAM

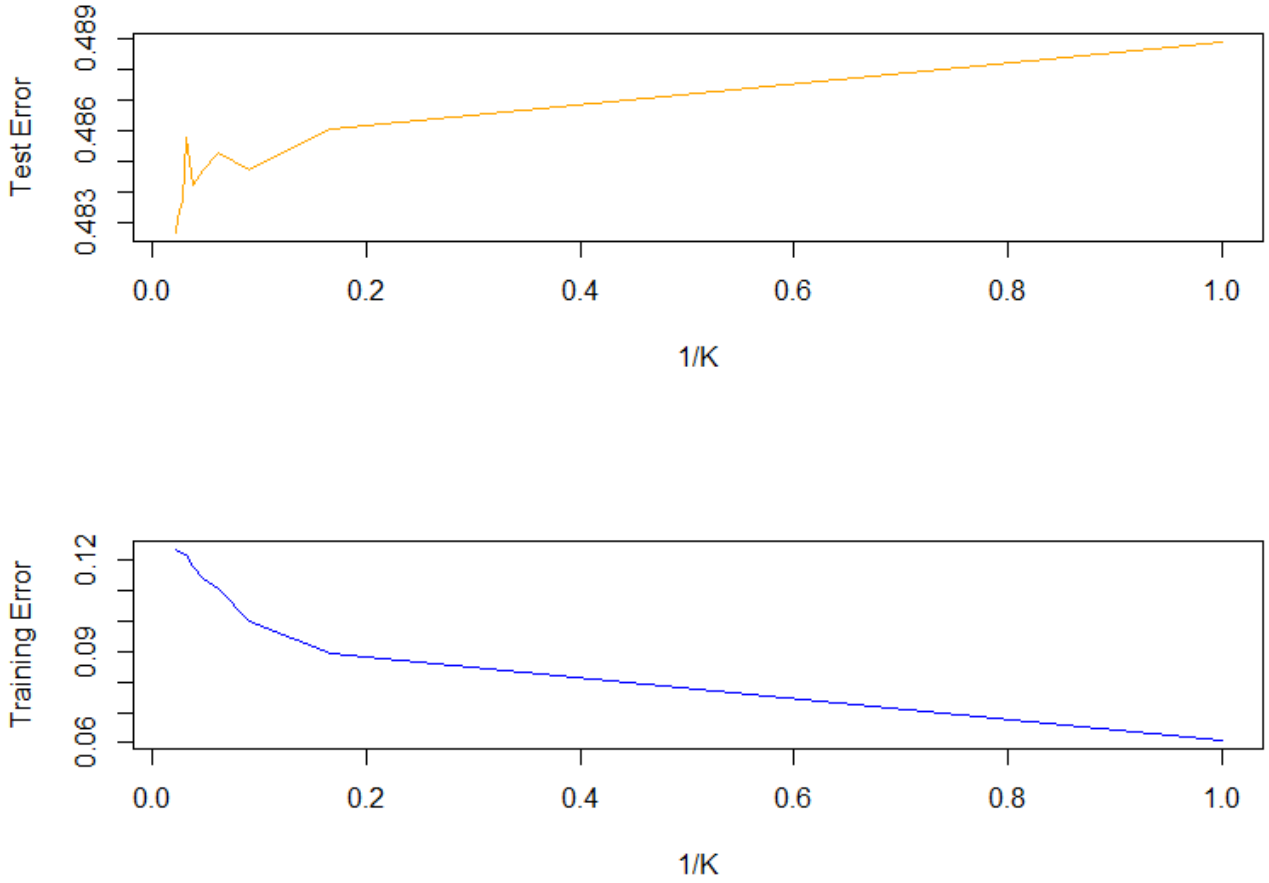

Figure A.6: KNN Training and Test Error

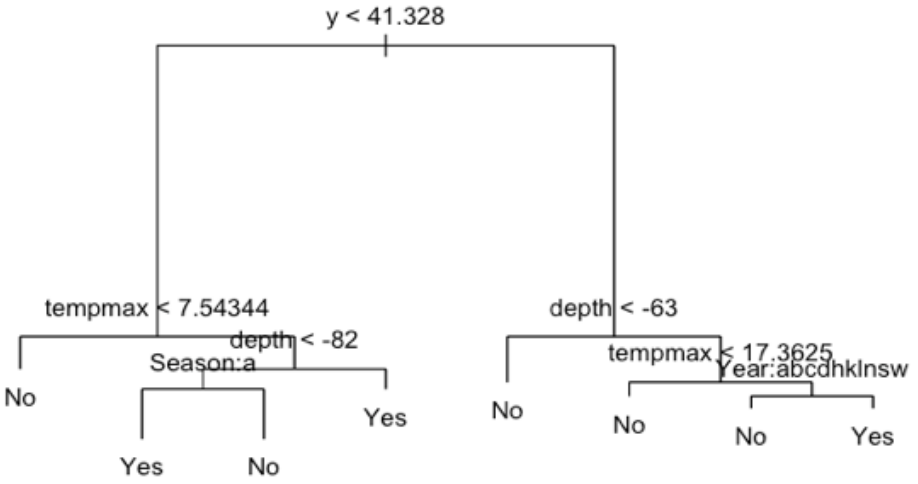

Figure A.7: Decision Tree

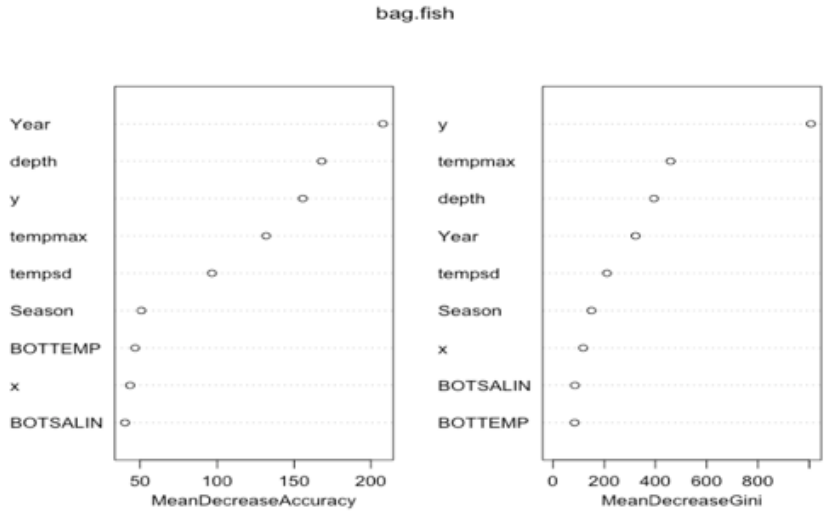

Figure A.8: Bagging Tree

A.4 Exploring Space-Time Models

A.4.1 Models

Linear Effect of Time: Model 1

The classic parametric formulation with the linear predictor is,

$$\eta_i = \alpha + \upsilon_i + \nu_i + (\beta_1 x_{1i} + \delta_i) \times t \tag{A.1}$$

where $\zeta_i = \upsilon_i + \nu_i$ are the spatial structured and unstructured components, β is the linear trend (time effect), and δ is the differential trend (interaction between space and time). If $\delta_i < 0$ then the area-specific trend is less steep than the mean trend, where the specification (Model 1) assumes a linear effect of time for each area (δ_i). The parameters estimated by INLA are $\theta = \alpha, \beta, \zeta, \upsilon, \delta$ and hyper parameters are represented by $\psi = \tau_\upsilon, \tau_\nu, \tau_\delta$.

Temporally Structured Effect: Model 2

The non parametric formulation for the linear predictor where the assumption of linearity in the differential temporal trend δ_i is relaxed, using a dynamic nonparametric formulation (Model 2) as

$$\eta_{it} = \alpha + \upsilon_i + \nu_i + \gamma_t + \phi_t \tag{A.2}$$

Where α, υ_i and ν_i have the same parameterization as Model 1, instead, γ_t represents the temporaly structured effect modeled dynamically using a random walk of order 1 (RW1) $\gamma_t|\gamma_{t-1}$ $Normal(\gamma_{t-1}, \sigma^2)$, or random walk of order 2 (RW2) $\gamma_t|\gamma_{t-1}, \gamma_{t-2}$ $Normal(2\gamma_{t-1} +$

$\gamma_{t-2}, \sigma^2)$. The parameter ϕ_t is specified by means of a Gaussian exchangeable prior: ϕ_t $Normal(0, \frac{1}{\tau_t})$. In this formulation $\theta = \alpha, \zeta, \upsilon, \gamma, \phi$ and the hyper parameters are represented by $\psi = \tau_\upsilon, \tau_\nu, \tau_\gamma, \tau_\phi$.

Spatial and Temporal Interactions: Model 3 - Model 6

The two parameters for the temporal trend (γ_t and ϕ_t) can be combined through a linear combination $1 \times \gamma_t + 1 \times \phi_t$ for each year. Model 2 can be modified to allow for a space and time interaction that would explain the differences in time trend for summer flounder abundances in different regions i,

$$\eta_{it} = \alpha + \upsilon_i + \nu_i + \gamma_t + \phi_t + \delta_{it} \tag{A.3}$$

where the two unstructured effects (independent identically distributed errors) ν_i and ϕ_t interact (Model 3). This is based on the assumption that there is no spatial and/or temporal structure on the interaction where $\delta_{it} \sim Normal(0, \tau_\delta)$. In this model $\theta = \alpha, \zeta, \upsilon, \gamma, \phi, \delta$ and $\psi = \tau_\upsilon, \tau_\nu, \tau_\gamma, \tau_\phi, \tau_\delta$.

Model 4 combines the structured temporal main effect γ_t and the unstructured spatial effect ν_i. Model 5 combines unstructured temporal effect ϕ_t and the spatially structured main effect υ_i. Model 6 is the most complex and combines the spatially υ_i and temporally γ_t structured effects (See Table 2.1).

A.4.2 Results

We have analyzed the abundances of summer flounder for Spring and Fall trawl surveys 1991-2015. The abundance is in $log(summerflounder)$ (Albatross Units). We implemented six different model specifications, linear models, models without space-time interaction, and models with at least one of the four interaction priors.

The first model has two parameters representing the temporal trend (γ and ϕ) reported on the natural scale. The unstructured term shows fluctuations around 1, whereas after fluctuating along 1, the structured effect declines rapidly after 2010 (Figure A.9).The residuals in the linear spatial model without interaction indicate autocorrelation, even though it had the lowest DIC.

We explore the space-time interactions to see if the residuals normalize. The non-parametric dynamic space-time model does not have a linearity constraint on the differential temporal trend δ_i Blangiardo and Cameletti (2015); Knorr-Held (2000). The interaction effects of space and time can be modeled assuming that the spatial (υ_i) and temporal (γ_t) effects interact. We use the formulation in Blangiardo and Cameletti (2015) transforming it to a spatio-temporal ecological regression by incorporating the relevant covariates (temperature, bottom salinity, depth) that explain the presence of summer flounder.

The residuals in Figure A.10 from Model 6 are more scattered than the simpler space-time models. These results also suggest that the remaining variation in the residuals can be further explained by unknown explanatory variables. The posterior mean of the spatial-temporal interaction γ_t for fluke incidence under the spatially and temporally structured interaction are in the Figure A.11.

We interpret the spatial, temporal and spatio-temporal effects as the residual effects,

after accounting for maximum surface ocean temperature, bottom salinity, depth. Between 2010 and 2015 we see that fewer administrative regions become dark, which is corresponding to the main (inverse quadratic) temporal trend in Figure A.9.

The posterior predictive check has two quantities of interest, (1) the posterior predictive distribution $p(y_i^*|y) = \int p(y_i^*|\theta_i)p(\theta_i|y)\,d\theta_i$ representing the likelihood of a replicate observation y_i^* having observed data y, (2) the posterior predictive p-value as $p(y_i^* \leq y_i|y)$. With values of $p(y_i^* \leq y_i|y)$ close to 0 or 1 are indicative of the model not fitting the data. Figure A.12 shows the scatter plot of the posterior mean for the predictive distributions for Model 6 against the observed values of summer flounder and the posterior predictive p-value . This is a scatter plot of the posterior mean for the predictive distributions against the observed values. The histogram is the posterior predictive p-value. The model predictions are close to the observed values. For the posterior p-value there most of the areas with a p-value in the middle range, suggest that the model fits the data reasonably well.

The fixed effects $(\alpha, \beta_1, \beta_2, \beta_3, \beta_4)$, are presented in Table A.4 and Table A.5. If exponentiated they can be interpreted as relative incidences of fish presence. During the Spring season, an increase of 1 unit °C in the sea surface temperature is associated with an increase of around $1\% = \exp(0.0149)$ in the incidence of summer flounder. During the Fall season, an increase of 1 unit °C in the sea surface temperature is associated with an increase of around $0.98\% = \exp(-0.0134)$ in the incidence of summer flounder.

The Model 5 estimates are very similar for the actual mean abundance of the summer flounder (Table A.4 and Table A.5). A results comparison of the models with the space-time interaction demonstrates that there is a relationship between summer flounder abundance and temperature (Figure **??**). We select two years to see the actual and predicted $log(y)$ (Figure **??**).

The more important question that we need to address is whether temperature, depth and bottom salinity are biologically important covariates in predicting the spatial temporal abundance of the summer flounder.

We also do a comparison of the CAR (Bivand) and the INLA Spatial Model, which also embeds a CAR to capture the spatially structured effects. We pick the year 1991, with no explanatory variables, just to take into account spatial auto-correlation. The intercepts are comparable, although, as expected the standard error on the R-INLA model is substantially lower than the CAR specification from Bivand (2007).

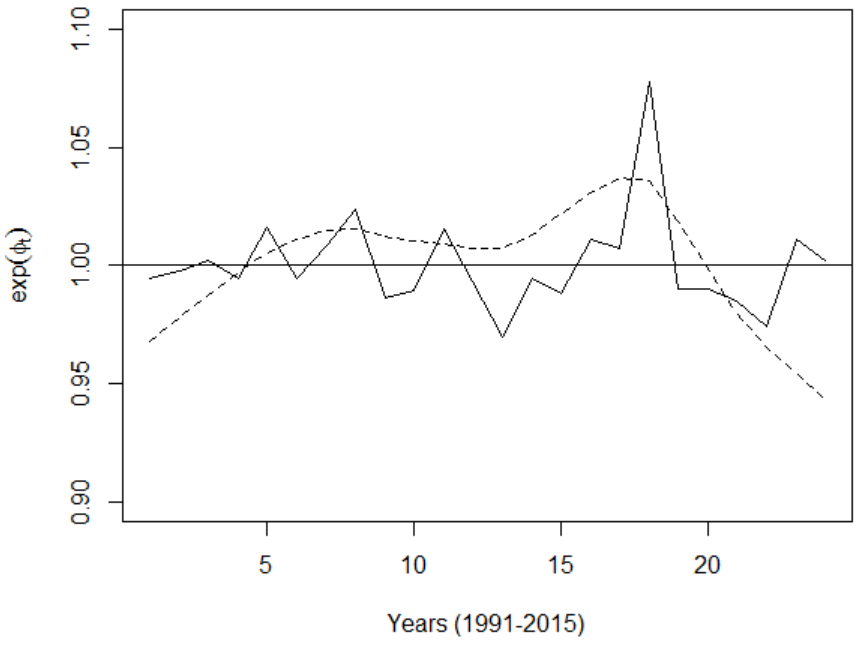

Figure A.9: Posterior trend for ALB: unstructured effect (solid line), temporally structured effect (dashed line) (Model 1)

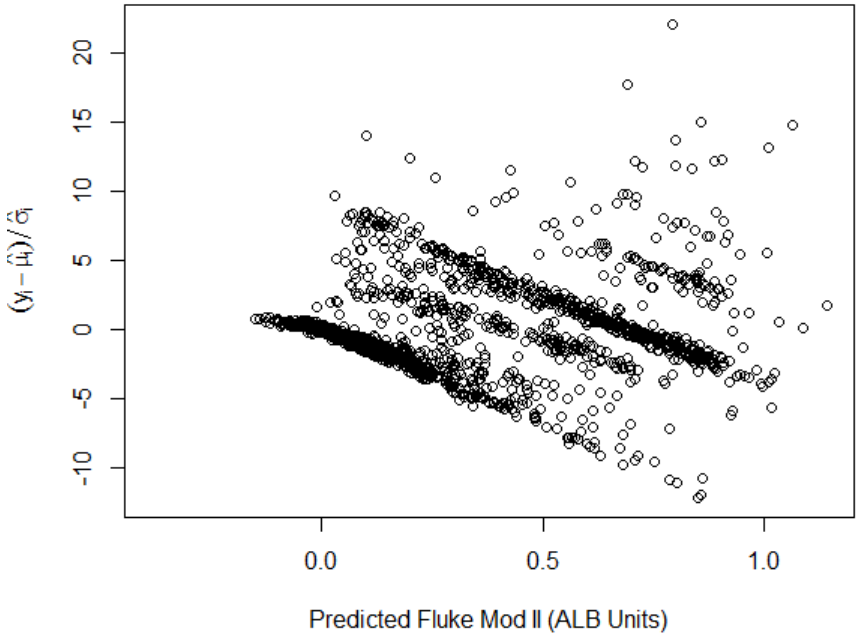

Figure A.10: Residuals from Model 6

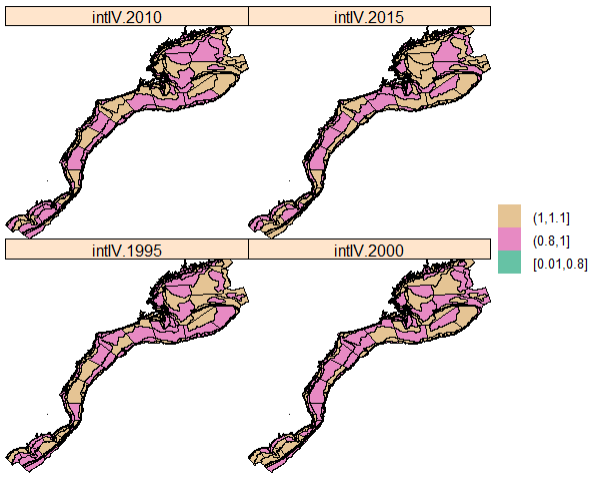

Figure A.11: Posterior mean of the spatio-temporal interaction $\delta_{I,t}$ for log(fluke) abundance (ALB Units) under the spatially and temporally structured interaction

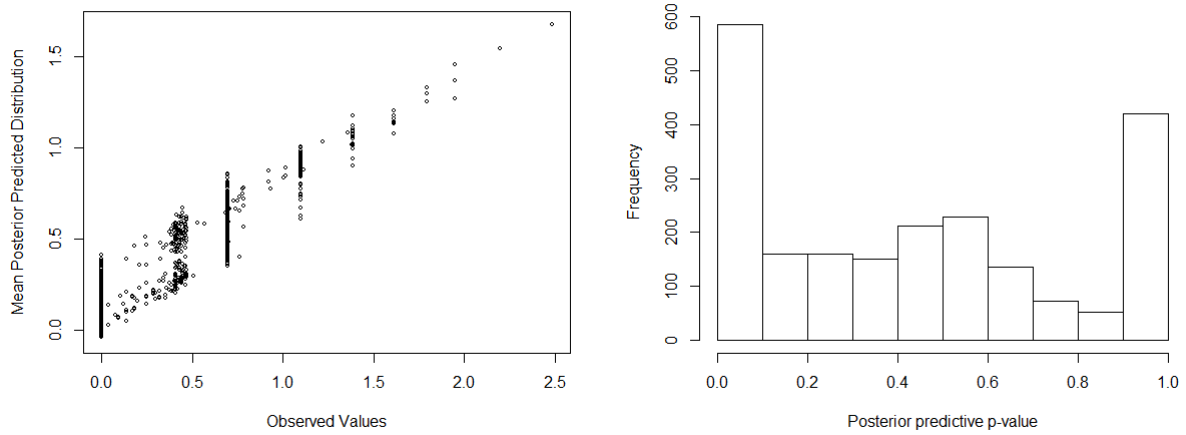

Figure A.12: Scatter plot of the posterior mean for the predictive distributions against the observed values (top). Histogram of the posterior predictive p-value (Model 6) (bottom)

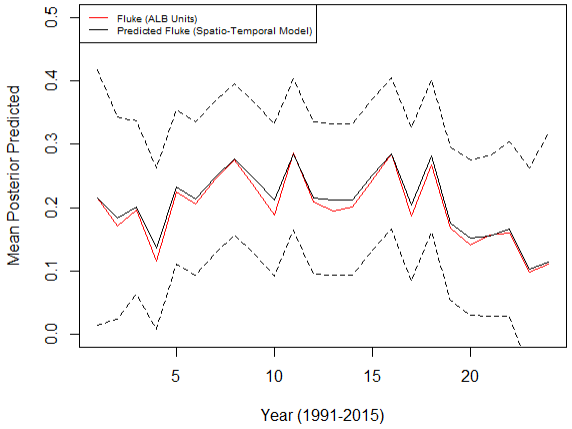

Figure A.13: Predicted Mean Abundance (black) and the Actual Mean Abundance (red) Model 6

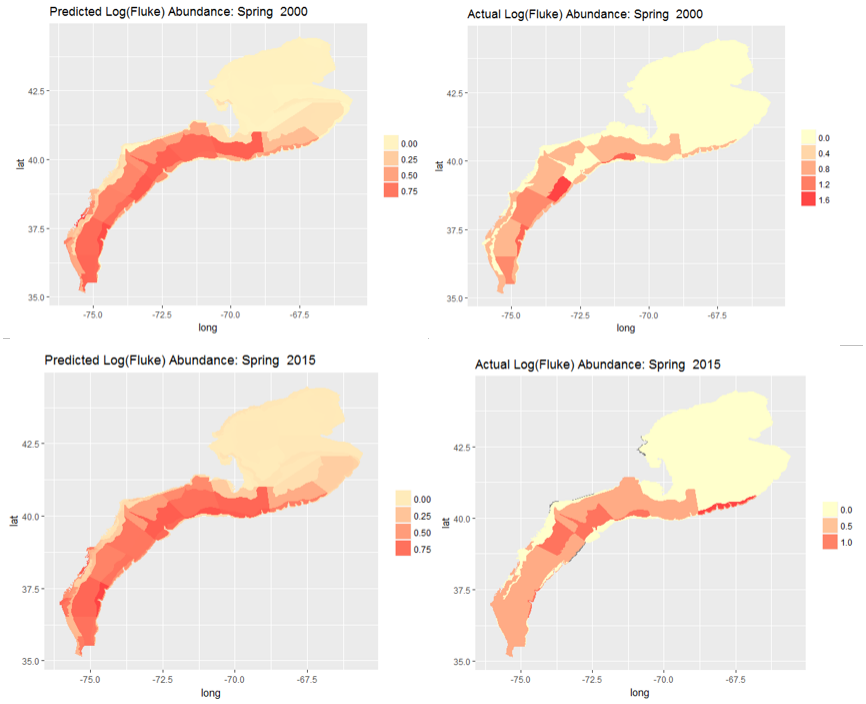

Figure A.14: Predicted vs Actual Fluke Abundance (ALB Units) Model 6

Table A.4: Summary statistics: posterior mean, posterior standard deviation (SD) for the fixed effects of the ecological regression model- Spring Trawl Survey log(Fluke Abundance)

	Model 3		Model 4		Model 5		Model 6	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	-0.4235	0.2965	0.0426	0.1209	-0.4804	0.3142	-0.2071	6.3979
Intercept	0.0096	0.006	0.0085	0.0089	0.0101	0.0061	0.0122	0.011
TempMax	0.0206	0.009	0.0037	0.0036	0.0223	0.0095	5e-04	0.069
Bottom Salinity	5e-04	2e-04	1e-04	9e-04	5e-04	2e-04	0.013	0.0095
TempMax^2	3e-04	3e-04	2e-04	4e-04	3e-04	3e-04	0	5e-04
DIC	-58.6453	-	441.4335	-	430.3108	-	-	434.8604

Table A.5: Summary statistics: posterior mean, posterior standard deviation (SD) for the fixed effects of the ecological regression model- Fall Trawl Survey log(Fluke Abundance)

	Model 3		Model 4		Model 5		Model 6	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	0.8523	0.5231	1.0954	0.5209	-0.4804	0.3142	1.0906	0.5193
Intercept	0.1737	0.0667	0.1425	0.0662	0.0101	0.0061	0.1434	0.0661
Bottom Temperature	-0.031	0.0161	-0.0387	0.016	0.0223	0.0095	-0.0386	0.0159
Bottom Salinity	1e-04	1e-04	1e-04	1e-04	5e-04	2e-04	1e-04	1e-04
depth	-0.0037	0.002	-0.0028	0.002	3e-04	3e-04	-0.0028	0.002
DIC	133.7576	-	575.448	-	430.3108	-	563.3585	-

APPENDIX B

GREEN SEA URCHIN

B.1 Effort

The aggregated level of effort is estimated by disaggregated ratio of licenses between draggers and divers by $Zone_i$, where

$$\begin{aligned} E_{1,t} &= \alpha_{1,D} L_{1,D,t} + \alpha_{1,B} L_{1,B,t} \\ Y_{1,t} &= q_1 X_{1,t} (\alpha_{1,D} L_{1,D,t} + \alpha_{1,B} L_{1,B,t}) \\ \frac{Y_{1,t}}{X_{1,t}} &= q_1 (\alpha_{1,D} L_{1,D,t} + \alpha_{1,B} L_{1,B,t}) + \epsilon_t \end{aligned} \tag{B.1}$$

where $L_{i,D,t}$ is the number of licenses in $Zone_i$ owned by draggars in year t, and $L_{i,B,t}$ is the number of licenses in $Zone_i$ owned by divers in year t. We assume $q = 0.014$ based on Chen et al. (2003) estimates. We run the linear regression,

$$\frac{Y_{1,t}}{X_{1,t}} = q_1 \alpha_{1,D} L_{1,D,t} + q_1 \alpha_{1,B} L_{1,B,t} + \epsilon_t \tag{B.2}$$

to estimate $\beta_{1,D} = q_1 \alpha_{1,D}$ and $\beta_{1,B} = q_1 \alpha_{1,D}$. The estimated aggregated effort by Zone and year is summarized in Table B.1. The Durbin Watson test rejects the alternative hypothesis for the presence of serial auto-corelation in the estimates of effort. The starting values of the aggregated estimated effort will be used for the determining the optimal closure and fisihing mortality.

Table B.1: Estimating Aggregated Effort

	Year	$Drag_1$ [a]	$Drag_2$	X_1 [b]	X_2	$Dive_1$	$Dive_2$	Y_1 [c]	Y_2	Y_1/X_1	Y_2X_2	E_1 [d]	E_2
1	1995	237	404	11978	18312	614	585	7021	6705.00	0.59	0.37	36.52	43.28
2	1996	167	327	8339	15746	503	566	4805	6016.00	0.58	0.38	47.65	30.29
3	1997	133	287	6038	13109	406	516	3138	4550.00	0.52	0.35	39.63	25.60
4	1998	95	260	5152	11577	349	461	2765	4811.00	0.54	0.42	46.69	23.52
5	1999	87	252	4502	9724	334	439	2385	3991.00	0.53	0.41	47.24	23.20
6	2000	74	242	3719	8401	315	409	2148	3213.00	0.58	0.38	49.81	22.92
7	2001	65	240	2223	5852	283	385	1524	2037.00	0.69	0.35	45.72	23.79
8	2002	53	242	1305	5860	248	344	921	2118.00	0.71	0.36	42.65	26.25
9	2003	44	224	716	5633	184	290	612	2261.00	0.85	0.40	28.59	25.76
10	2004	30	206	280	5033	136	262	71	1647.00	0.25	0.33	22.78	23.93
11	2005	27	187	307	4867	107	235	51	1697.00	0.17	0.35	15.70	21.87
12	2006	24	178	361	4467	83	214	70	1304.00	0.19	0.29	10.18	21.31
13	2007	21	164	421	4290	78	196	81	1350.00	0.19	0.31	10.59	19.69
14	2008	18	163	446	3957	64	189	63	1343.00	0.14	0.34	8.18	19.87
15	2009	18	152	498	3597	60	182	55	1357.00	0.11	0.38	6.94	18.24
16	2010	15	157	526	3186	57	169	67	977.00	0.13	0.31	7.96	19.81
17	2011	16	159	601	3121	48	157	82	975.00	0.14	0.31	4.51	20.79
18	2012	15	143	697	2985	48	148	124	710.00	0.18	0.24	5.16	18.35
19	2013	15	134	724	2983	51	130	174	698.00	0.24	0.23	6.09	17.64

[a] Number of licensed draggers in $Zone_1$
[b] Biomass (metric tons)
[c] Harvest (metric tons)
[d] Predicted Effort in $Zone_1$

B.2 Catchability coeficient

The catchability coefficient q is estimated using the Shaeffer production function and the Spence production function (Table B.2 and Table B.3). Using the known harvest, and estimated biomass in Hunter (2015). We can estimate the catchability coefficient, q using two separate production functions. The Schaeffer production function,

$$\begin{aligned} Y_t &= qX_tE_t \\ ln(Y_t) &= ln(q) + ln(X_t) + ln(E_t) \\ ln(Y_t) &= \beta_0 + \beta_1 ln(X_t) + \beta_2 ln(E_t) \end{aligned} \tag{B.3}$$

and the Spence production function.

$$
\begin{aligned}
Y_t = X_t(1 - e^{-qE_t}) \; (Y_t/X_t) = 1 - e^{-qE_t} \\
e^{-qE_t} = 1 - (Y_t/X_t) = (X_t - Y_t)/X_t \\
ln[(X_t - Y_t)/X_t] = -qE_t ln[(X_t - Y_t)/X_t] = \beta_0 + \beta_1 E_t
\end{aligned}
\tag{B.4}
$$

In regression (B.3) we would hope that $\beta_0 = ln(q)$ or $q = e^{\beta_0} > 0$, but small (for example 1.0×10^{-5}), and $\beta_1 \approx \beta_2 \approx 1$ or not significantly different from 1. In regression (B.4) we hope $\beta_0 \approx 0$ (and not statistically different from 0) and that $\beta_1 < 0$ and small. The results of the regression (B.3), $\beta_0 = 0.02$, $\beta_1 = 1.09$, $\beta_2 = 0.6$ (Table B.2). The results of the regression (B.4) $\beta_0 = 0.6$ and $\beta_1 = --0.4125$ (Table B.3). These are estimates for Zone 1. The $\beta_0 = 0.02$ is close to the $q = 0.014$ estimate in Chen et al. (2003).

Table B.2: Estimating q: Shaeffer Production Function

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-3.5908	0.4486	-8.00	0.0000
lnX	1.0901	0.0891	12.23	0.0000
lnE	0.6111	0.1235	4.95	0.0001

Table B.3: Estimating q: Spence Production Function

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.6167	0.2758	2.24	0.0390
lnE	-0.4125	0.0908	-4.54	0.0003

B.3 Urchin Parameter Estimates

Stage	Parameter	Source
Eggs		
	100,000-200,000 per female	Sullivan 1995
	Fertilization rate 50-90%, 50-85%	Brady and Scheibling (2006); Kregting et al. (2013)
	Fertilization to larval stage 48+ hours -20 days (maximum plutues without feeding at 4°C), 90-95% eggs fertilizable within $1-2$ days, fertilization rate 10% after 7 days	Lamare and Stewart (1998); Stephens (1972)
Larva		
	Settlement rate 50-90%	Gaylord et al. (2013)
	Settlement 21 weeks or 50-63 days from fertilization, planktonic stage lasts 23-70 days	Seward (2002); Strathmann (1978)
	Pelagic larval stage 3 - 21 weeks (51-152 days / 5 months) from time of fertilization to settlement. Depends on food availability and temperature.	Seward (2002); Strathmann (1978)
	In Woods hole larval development in 9 weeks at 4-7°C, and shorter under higher temperatures.	
	Settlement between the month June-July	Lambert and Harris (2000)
	Dispersal rates (no data). Based on oceanographic currents in the Gulf of Maine, loss of larva through dispersal maybe lower in Zone 2 compared to Zone 1. Larval dispersion from Zone 2 to Zone 1 is plausible.	
	10°C is the upper limit for larval development (under laboratory conditions) Survival in high organic content is also substantially reduced.	Stephens (1972)

Juvenile		
	Mortality rate 33-45%, 50%	Dupont, Dorey, Stumpp, Melzner, and Thorndyke (2013); Vavrinec (2003)
	9-13°C optimal temperature	Pearce, Daggett, and Robinson (2002)
	Juvenile size at settlement 0.5mm, age 0 <10mm	Russell et al. (1998)
Adult		
	Maturity 2.75-3 years post spawning	Munk (1992); Raymond and Scheibling (1987)
	Size at sexual maturity 25mm, 18-33mm	Brady and Scheibling (2006); Munk (1992)
	Annual survival rates 74-96%	Russell et al. (1998)
	Immature urchins 4-11mm	Munk (1992)
	Spawning period in early Spring (March-April) at 4-6°C. In food-rich regions a second spawn in late Summer (June-November)	Brady and Scheibling (2006); Himmelman (1978); Keats, Steele, and South (1984)
	Central Maine Spawning occurs late February March (60+ days) 5-6°C. Eastern Maine Spawning occurs April May ($34-50$ days) 4-5°C	Seward (2002); Vadas et al. (2015)
	Between 55% and 77% of the variation in mean Gonad Index can be explained by seawater temperature differences in Maine between Zone 1 and Zone 2	Townsend, Rebuck, Thomas, Karp-Boss, and Gettings (2010); Vadas et al. (2015)
	Cape Cod mid March mid April, 99% fertilization rate in 9/10 females. In cold winters fertility extends into May. Maine fertility period 2 weeks mid April.	Stephens (1972)

Body size groups small (S, 40 g = 0.09 lbs), medium (M, 65 g = 0.14lbs), and large (L, 100 g = 0.22lbs)	Siikavuopio et al. (2008)
Urchins reach sexual maturity at 10 g approx. size 30mm	Hunter (2015)

Table B.4: Biological Parameter Estimates

APPENDIX C

CORAL BLEACHING IN INDONESIA

C.1 Robustness Checks

In Table C.1 I show that the results are robust to the inclusion of control variables that are known to impact malnutrition in fisher villages. While thermal threats are significantly correlated with malnutrition, the interaction effects of thermal and local threats have a higher β coefficient, that is statistically significant as well.

Table C.1: Thermal and Local Threats - Malnutrition in Fisher Communities (Full Sample)

	Dependent variable: Log(Malnutrition)					
	(1)	(2)	(3)	(4)	(5)	(6)
Thermal Threat	0.0001***	−0.00002	0.0001***	0.0001***	0.0001***	0.00003
	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.0001)
Kecamatan Specific Fixed Effects		×				
Village Level Capital Assets			×		×	×
Village Level Human Capital				×	×	×
Natural Assets					×	×
Local Threat × Thermal Threat						3.559
						(2.435)
(Local Threat × Thermal Threat)^2						2.595***
						(0.940)
Observations	1,749	1,749	1,749	1,749	1,749	1,749
R^2	0.007	0.660	0.051	0.066	0.074	0.112
Adjusted R^2	0.007	0.449	0.043	0.058	0.065	0.097

Note: Standard errors shown in parenthesis. Statistical significance is represented by: *p<0.1; **p<0.05; ***p<0.01

C.2 Determinants of Malnutrition

Table C.2 reports the results of the linear regression models. Column 1 and 2 describe the coefficients on the determinants of log(number of malnutrition cases) reported in fisher dominant villages. The coefficient on the interaction variable thermal threats and local threats is 0.087, which means that the thermal threats in regions with poor water quality, coastal development, pollution, and increased fishing pressure will increase the number of malnutrition by 9 percentage points. The control variables in general have the expected signs. *Desas* with more motor boats tend to have higher malnutrition cases. *Desas* with higher local or global (thermal threats) have higher cases of malnutrition. Villages with lower opportunities to sell their agricultural and fish produce are poorer. Lower percentage of households with electricity, hospitals, and schools are expected to have higher cases of malnutrition. *Desas* with higher incidence of malnutrition are also located in remote regions where deforestation rates are lower. Social disruption such as crime incidences are also lower in remote villages with high malnutrition rates.

Column 3 and 4 describe the effect of thermal threats on the presence or absence (extensive margin) of malnutrition cases reported. As expected, we see that the presence of malnutrition has a negative relationship with forest loss, water clarity, and water pollution. More important local and thermal threats are positively associated with malnutrition. As mentioned earlier, the local threats are a composite of coastal development, watershed-based pollution, marine-based pollution and damage, overfishing and destructive fishing, and the global threats are a composite of thermal stress.

Table C.2: Determinants of Malnutrition in Fisher Communities (Full Sample)

	Dependent variable:			
	ln.malnutrition		is.malnutrition	
	OLS		*logistic*	
	(1)	(2)	(3)	(4)
Mean Chlorophyll-a near Village (2008)		−0.011**		
		(0.005)		
Water Pollution (Yes = 1, No = 0)		0.151**		
		(0.065)		
Local Threats (Index)		−0.001**		−0.004**
		(0.001)		(0.002)
Thermal Threats (Index)				−0.001***
				(0.0004)
Soil Pollution		0.276*		0.651
		(0.158)		(0.424)
Land Burnt (ha)		0.001		0.006*
		(0.001)		(0.003)
Presence of Toilets		0.056***		0.146***
		(0.015)		(0.041)
Rice Land (ha)		−0.001		
		(0.0003)		
Cell Phone Signals (Strong)				0.209
				(0.133)
Houses with Electricity (%)		−0.802***		−2.712***
		(0.218)		(0.686)
Schools (%)		−35.646***		−106.461***
		(12.464)		(38.321)
Number of Families with Insurance Cards		0.0004***		0.001**
		(0.0001)		(0.0002)
Land being converted to non-agricultural land (ha)		0.147***		0.323**
		(0.048)		(0.127)
Number of Incidences of Measles		0.014***		0.038**
		(0.004)		(0.015)
Number of Incidences of Dengue		−0.009**		−0.024*
		(0.004)		(0.014)
Death from Avian Flu		0.103*		
		(0.055)		
Number of Incidences of Avian Flu		−0.002*		
		(0.001)		
Number of Incidences of Diarhoea		0.005***		0.007*
		(0.002)		(0.004)
Presence of Crime (High = 4, Low = 0)		−0.086***		−0.285***
		(0.025)		(0.065)
Remoteness (Some)		−0.120*		−0.370**
		(0.065)		(0.185)
Total number of Village level Cooperatives		0.036***		0.059
		(0.013)		(0.037)
Log (Forest Loss)		−0.001		0.280*
		(0.027)		(0.154)
Log (Forest Loss)^2		0.003		0.102**
		(0.004)		(0.048)
Log (Forest Loss)^3				0.008**
				(0.004)
(Mean Chlorophylla)^2				−0.010***
				(0.003)
(Mean Chlorophylla)^3				0.0002***
				(0.0001)
(Local Threat)^2		0.00000**		0.00001***
		(0.00000)		(0.00000)
(Local Threat)^3		−0.000***		−0.000***
		(0.000)		(0.000)
(Thermal Threat)^2		−0.00000***		0.00000***
		(0.00000)		(0.00000)
(Thermal Threat)^3		0.000***		
		(0.000)		
(Local ×Thermal Threat)^2	0.087***	0.076**	0.173***	0.147*
	(0.016)	(0.030)	(0.038)	(0.083)
Constant	0.414***	2.328***	−0.908***	5.925***
	(0.026)	(0.550)	(0.065)	(1.469)
Observations	1,749	1,749	1,749	1,749
R^2	0.018	0.127		
Adjusted R^2	0.017	0.114		
Akaike Inf. Crit.			2,189.738	2,073.391

Note:Standard errors shown in parenthesis. Significance levels: *p<0.1; **p<0.05; ***p<0.01

C.3 Thermal and Local Threats

The interaction effects of thermal and local threats have been captured in Figure C.1 through Figure C.5.

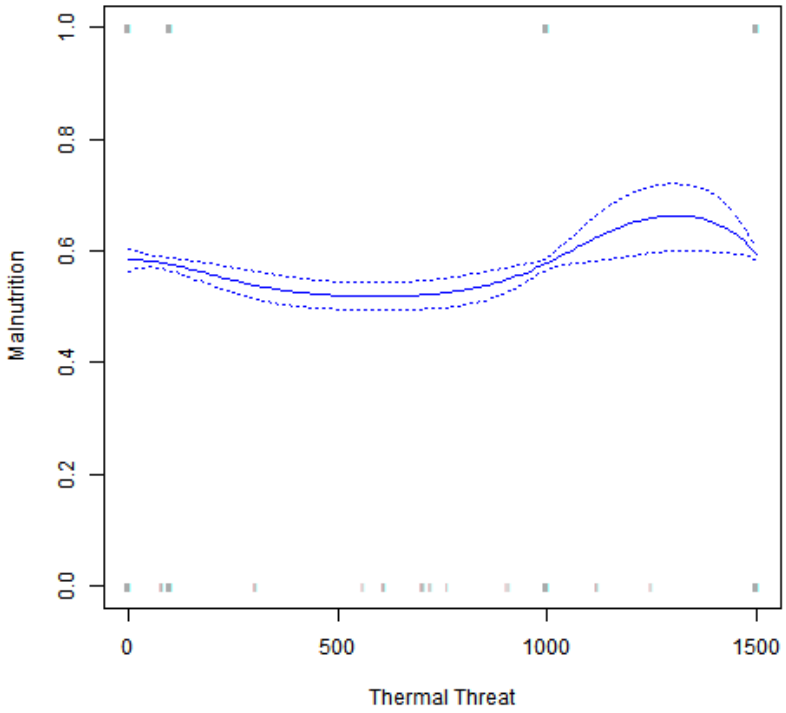

Figure C.1: Polynomial of Thermal Threats and log(malnutrition) cases in coastal wild-capture fisher villages in Indonesia (2008)

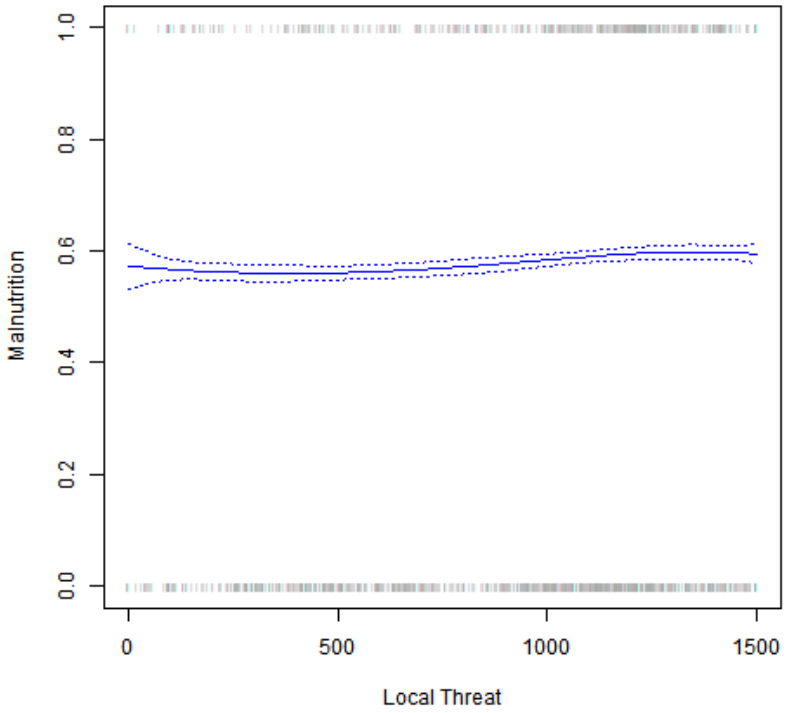

Figure C.2: Polynomial of Local Threats and log(malnutrition) cases in coastal wildcapture fisher villages in Indonesia (2008)

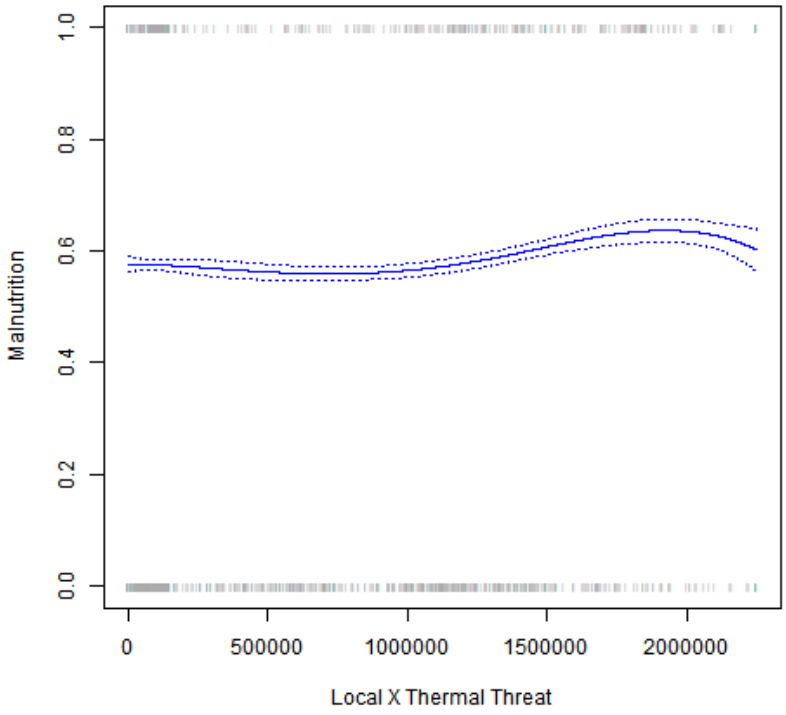

Figure C.3: Polynomial of Local × Thermal Threats and log(malnutrition) cases in coastal wild-capture fisher villages in Indonesia (2008)

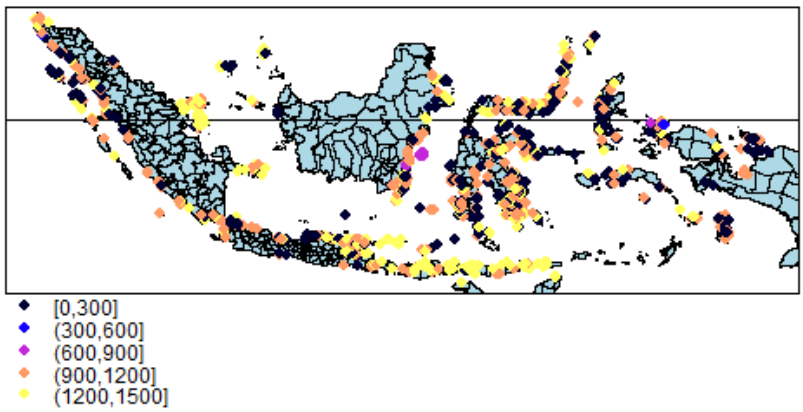

Figure C.4: Thermal threats to coastal wild-capture fisher villages in Indonesia

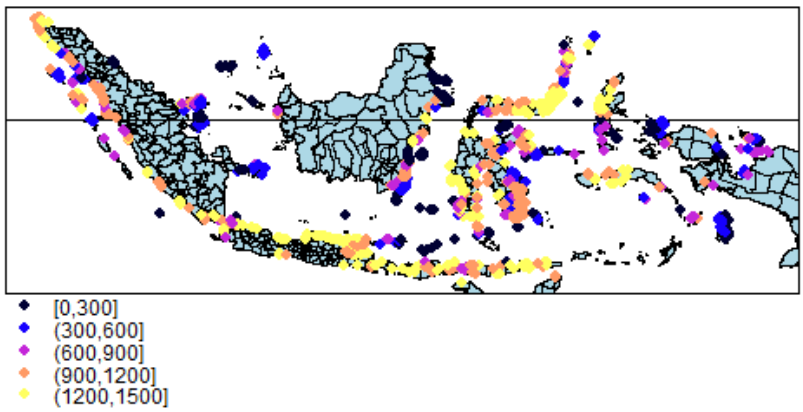

Figure C.5: Index of local threats to coastal wild-capture fisher villages in Indonesia

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